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Applying ABC analysis to the Navy's inventory management system

May, Benjamin

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THESIS

APPLYING ABC ANALYSIS TO THE NAVY'S INVENTORY MANAGEMENT SYSTEM

by

Benjamin May

September 2014

Thesis Co-Advisors:	Michael P. Atkinson Geraldo Ferrer
Second Reader:	Samuel Buttrey

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ABC Analysis is an inventory categorization technique used to classify and prioritize inventory items in an effort to better allocate business resources. "A" items are defined as the inventory items considered extremely important to the business, requiring strict oversight and control. "B" items are important to the business, but don't require the tight controls and oversight required of the "A" items. "C" items are marginally important to the business. ABC Analysis aims to ensure the business-driving inventory items are effectively and efficiently managed.

There are numerous single- and multiple-criteria approaches to implementing ABC Analysis. This thesis presents an analysis and comparison of multiple approaches, as they relate to Navy Weapons Systems Support (WSS) Command's large National Item Identification Number (NIIN) inventory. Additionally, random forests are grown from the inventory metadata to identify and/or verify the attributes most strongly affecting fleet readiness goals. The model will allow WSS to focus resources not only on the correct NIINs, but in the correct areas of NIIN management. Better WSS resource allocation will result in higher fleet readiness, WSS's primary goal.

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APPLYING ABC ANALYSIS TO THE NAVY'S INVENTORY MANAGEMENT SYSTEM

Benjamin May
Lieutenant Commander, Supply Corp, United States Navy
B.S., East Carolina University, 2003

Submitted in partial fulfillment of the
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September 2014

Author: Benjamin May

Approved by: Michael P. Atkinson
Thesis Co-Advisor

Geraldo Ferrer
Thesis Co-Advisor

Samuel E. Buttrey
Second Reader

Robert F. Dell
Chair, Department of Operations Research

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TABLE OF CONTENTS

I. INTRODUCTION....1
- A. BACKGROUND....1
- B. ABC ANALYSIS....4
- C. THESIS PURPOSE....6

II. LITERATURE REVIEW....7
- A. ABC MODEL VARIANTS....7
  1. Joint-Criteria Matrix....7
  2. MUSIC-3D....8
  3. Operations-related Groups....9
  4. Analytic Hierarchy Process....9
  5. Genetic Algorithm for Multi-Criteria Inventory Classification....11
  6. Weighted Linear Optimization....13
  7. Simple Classifier for Multiple-criteria ABC Analysis....13
  8. Weighted Non-linear Optimization....14

III. DATA AND METHODOLOGY....17
- A. SCOPE....17
- B. DATA....20
- C. VARIABLE SELECTION....22
- D. VARIABLE ANALYSIS....27
  1. Fill Rate....28
  2. Demand....28
  3. Lead Time....31
  4. Criticality....33
  5. Price....37
  6. Summary....39
- E. METHODOLOGY AND VARIABLES....40

IV. MODEL ANALYSIS....47
- A. MODEL....47
- B. MODEL RESULTS....49
- C. RESULTS OF ALTERNATIVE MODELS....50
  1. ABCD Prioritization....50
  2. Requisitions Volume Prioritization....53
  3. Dollar Usage Prioritization....54
  4. Criticality Prioritization....55
  5. Uniform Prioritization....55
- D. COMPARISON OF ALTERNATIVE MODELS....56
- E. SENSITIVITY ANALYSIS....64
- F. ANALYSIS OF WNO VERSUS ABCD ON FUTURE REQUISITIONS....66

V. CONCLUSION AND RECOMMENDATIONS....73

A. CONCLUSIONS 73
B. RECOMMENDATIONS...74
C. FUTURE RESEARCH...75

LIST OF REFERENCES 77

INITIAL DISTRIBUTION LIST 79

LIST OF FIGURES

Figure 1. Pareto Diagram (from Duffuaa, Raouf, & Campbell, 1999, p. 198). 4
Figure 2. Joint Criteria Matrix (from Flores and Whybark, 1987, p. 41)..........................8
Figure 3. MUSIC-3D matrix (from Gopalakrishnan, 2002, p. 167). 9
Figure 4. AHP Structure (from Flores, Olson, & Dorai, 1992, p. 74)............................10
Figure 5. Relative importance scale used for value assignments (from Flores, Olson, & Dorai, 1992, p. 74). 10
Figure 6. Pairwise comparison matrix (from Flores, Olson, & Dorai, p. 74). 11
Figure 7. Resulting formula from AHP process (from Flores, Olson, & Dorai, 1992, p. 74). 11
Figure 8. Sample structure of an ANN (from Partovi & Anandarajan, 2002, p. 392). ...12
Figure 9. Weighted linear optimization formula (from Ramanathan, 2006, p. 697).......13
Figure 10. SCMC criteria transformation formula (from Ng, 2007, p. 345)....................14
Figure 11. SCMC formulation, post-transformation (from Ng, 2007, p. 346).................14
Figure 12. SCMC process, post-transformation (from Ng, 2007, p. 348).........................14
Figure 13. Simple WNO formulation, post-transformation (from Hadi-Vencheh, 2010, p. 965). 15
Figure 14. Sample of a decision tree used to facilitate the underwriting process of mortgage applicants (from Rokach & Maimon, 2008, p. 7). 24
Figure 15. Random forest construction (from Benyamin, 2012) 25
Figure 16. Random forest results for growth of 1000 trees with fill rate as response and wholesale file metadata. 27
Figure 17. Fill Rate Distribution among full set of NIINs for the time period April 2011 through March 2014..28
Figure 18. Summary statistics for 36-month requisition totals and requisition sizes for each NIIN. 29
Figure 19. Summary statistics for repair survival rate and repair pipeline loss rate. 30
Figure 20. Summary statistics for 36-month quantity demand, demand sigma, regeneration demand, and attrition demand. 31
Figure 21. Summary statistics for procurement administrative lead time, production lead time, procurement lead time, and repair turnaround time. 32
Figure 22. Summary statistics for PPV and PPV variance...33
Figure 23. Summary statistics for 36-month whiskey requisitions, percentage of NIIN requisitions that were a whiskey, and the fill rate for whiskey requisitions. ...34
Figure 24. Summary statistics for 36-month High-Priority (Pri 1-3) requisitions and proportion of requisitions for each NIIN that are High Priority. 35
Figure 25. Summary statistics for NIIN Item Management Essentiality Codes. 37
Figure 26. Summary statistics for standard, net, replacement, and repair prices. 37
Figure 27. Summary statistics of discount and premium relationships between various price types, including net, standard, repair, and replacement. 38
Figure 28. WNO criteria transformation formula (from Ng, 2005, p. 345). 40
Figure 29. Simple WNO formulation, post-transformation (from Hadi-Vencheh, 2008, p. 965). 40

Figure 30. Sample of constraints used in the WNO model. 48
Figure 31. WNO's results, representing % coverage of total metric value for each specified number of highest priority NIINs. 50
Figure 32. Comparison of cumulative % of total criticality metric captured. 57
Figure 33. Comparison of cumulative % of total dollar usage captured. 58
Figure 34. Comparison of cumulative % of total whiskey requisitions captured. 59
Figure 35. Comparison of cumulative % of total requisitions captured...........................60
Figure 36. Comparison of cumulative % of total requisition variance captured. 61
Figure 37. Comparison of cumulative % of total quantity demand captured...................62
Figure 38. Comparison of cumulative % of total PPV captured. 63
Figure 39. Comparison of cumulative % of total PPV variance captured. 64
Figure 40. NIIN classification differences between WNO and ABCD models for requisitions from April through June of 2014...69
Figure 41. Fill rate measures for each category of the different classifications...............70

LIST OF TABLES

Table 1. Classification levels are set via historical 24-month demand data, 12-month CASREP data, and specified platform degraders 3
Table 2. Descriptions of ABC-derived inventory management techniques (from Gopalakrishnan, 2002, p. 165). 5
Table 3. Details of the six COGs included in the analysis. 19
Table 4. Requisition Priority Matrix (from NAVSUP P-485 vol. 1) 35
Table 5. Demand values for NIIN 000011632 over different time frames 42
Table 6. Criticality scores and rankings for 4 NIINs under three different scenarios 43
Table 7. Table of variables and associated attributes that are used to prioritize NIINs in WNO model. 45
Table 8. WNO's results, representing % coverage of total metric value for each specified number of highest priority NIINs. 49
Table 9. Classification levels are set via historical 24-month demand data, 12-month CASREP data, and specified platform degraders 51
Table 10. Results of ABCD prioritization, representing % coverage of total metric value for each specified number of highest priority NIINs. 52
Table 11. Results of NIIN prioritization based on ABCD instead of WNO, representing increase or decrease in % coverage of total metric value for each specified number of highest priority NIINs. 52
Table 12. Matrix shows the NIIN classification overlap between the WNO and ABCD models, using identical class sizes. 53
Table 13. Results of NIIN prioritization based on requisition volume instead of WNO, representing increase or decrease in % coverage of total metric value for each specified number of highest priority NIINs. 54
Table 14. Results of NIIN prioritization based on dollar usage instead of WNO, representing increase or decrease in % coverage of total metric value for each specified number of highest priority NIINs. 54
Table 15. Results of NIIN prioritization based on criticality instead of WNO, representing increase or decrease in % coverage of total metric value for each specified number of highest priority NIINs. 55
Table 16. Results of WNO NIIN prioritization using 24/12 (24 months of requisitions and 12 months of whiskey requisitions). 65
Table 17. Comparison results of WNO NIIN prioritization using 36/24 instead of 24/12. 65
Table 18. Comparison results of WNO NIIN prioritization using 18/6 instead of 24/12. 66
Table 19. Results of WNO NIIN prioritization using data from April 2011—September 2012. 67
Table 20. Results of WNO NIIN prioritization using data from October 2012—March 2014. 67

Table 21. Comparative results of using a requisition and whiskey volume prioritization model instead of the WNO model for two sequential 18-month timeframes. 68
Table 22. WNO model results, based on requisitions from April through June of 2014....................71
Table 23. ABCD model results, based on requisitions from April through June of 2014....................71

LIST OF ACRONYMS AND ABBREVIATIONS

ABC	Always Better Control
ADD	average delays days
AHP	Analytical Hierarchy Process
ANN	Artificial Neural Networks
CASREP	casualty report
COG	Cognizance Code
DOD	Department of Defense
DLR	Depot-level Repairable
ERP	enterprise resource planning
FAD	force activity designator
FIFO	First-in, First-out
FR	Fill Rate
FSN	Fast-Slow-Non Movement
GAMIC	Genetic Algorithm for Multi-criteria Inventory Classification
GOLF	Government-controlled, Ordinarily-available, Locally-available, Foreign-imported
GRG	Generalized Reduced Gradient
HCV	high-consumption value
HML	high-medium-low value
IMEC	Item Management Essentiality Code
LCV	low-consumption value
LLT	long lead time
LRT	Logistics Response Time
MCC	Mission Criticality Code
MCIC	Multi-Criteria Inventory Classification
MEC	Military Essentiality Code
MIME	Multi-indenture Multi-echelon
NAVSUP	Naval Supply Systems Command
NIIN	National Item Identification Number

ORG	operations-related groups
PBL	Performance-based Logistics
PPV	Procurement Problem Variable
RFI	Ready for issue
RPLR	Retrograde Pipeline Loss Rate
SCMC	simple classifier for multiple criteria
SDE	scarce or single-source item, difficult-easy to obtain
SLT	short lead time
SOS	seasonal & off-seasonal
SPO	service planning optimization
SUBSAFE	Submarine Safety
VED	Vital-Essential-Desirable Criticality
VEIN	Vital-Essential-Important-Normal Criticality
WLO	weighted linear optimization
WNO	weighted non-linear optimization
WSS	Weapons Systems Support

EXECUTIVE SUMMARY

Always Better Control (ABC) analysis is an inventory management technique based on Pareto's law which states that the significant items in a group usually constitute a small portion of the items in that group (Duffuaa, Raouf, & Campbell, 1999, p. 198). In early ABC analysis, inventory was prioritized based on its dollar usage, which is unit demand multiplied by unit price. Over time, the idea of managing inventory based on dollar usage has morphed into a strategy of managing inventory based on a multitude of criteria. Data analysis, simulation, and optimization have all been adopted by numerous ABC analysis techniques in an effort to tailor prioritization schemes to a variety of companies within a variety of industries.

Weapon Systems Support (WSS) aims to adopt and implement a new tailored ABC analysis approach to its inventory management process. Historically, WSS has managed procurement and repair contracts via a first-in, first-out method. WSS intends to improve its service to the fleet by boosting the efficiency and effectiveness at which it manages inventory. Service to the fleet can be improved by optimally managing the inventory items that contribute greatest to operational readiness, fill rate, and budget requirements.

Various ABC analysis techniques are considered for applicability to WSS processes and requirements. Each model offers its own pros and cons, including the way variables are determined and applied to inventory item prioritization. To determine the best fit for WSS, variable and/or metric selection for prioritization is required. The data analyzed consists of non-specialized maritime national item identification numbers (NIINs) requisitioned at least once over the three-year time frame from April 2011 through March 2014. The list of NIINs analyzed totals nearly 18,000. Because fill rate is the primary metric used to measure WSS effectiveness, it is the metric considered for regression analysis. Regression analysis, in the form of random forests, is conducted on the full dataset to determine the primary drivers of fill rate. Demand, price, and lead time are identified as those primary drivers.

In addition to fill rate drivers, a measure of criticality is representative of the importance of a part to operational readiness. Subject matter expertise is used to determine how to account for this vital measure in a modeling approach. A criticality measure is applied to each NIIN based on casualty report requisition volume, requisition priorities, and item management essentiality codes. This measure of criticality, coupled with measures of demand, price, and lead time, provides a suitable and accurate representation of an item's importance to operational readiness and fill rate.

Given the factors identified as important to any WSS NIIN-prioritization model, the multi-criteria weighted non-linear optimization (WNO) model proves to be the best option. The model accepts any number of NIINs and NIIN attributes. The attributes are subjectively ranked in terms of importance, which forces the weights of higher ranked attributes to be higher than those of lower ranked attributes. Weights are optimally assigned to priority-ranked NIIN attributes so as to maximize the sum of factor-based scores across all NIINs being ranked. This technique identifies the order in which NIINs should be optimally managed based on the priorities specified.

Based on the data analysis and subject matter expertise, a total of six factors are used to prioritize NIINs in the weighted non-linear optimization (WNO) prioritization model. In order of priority, they are criticality, dollar usage, requisition volume, requisition variance, procurement problem variable (PPV), and variance of PPV. PPV is a measure of demand over repair and procurement lead time. Once the model is run and the scores are generated, NIINs are priority-ranked based on those scores in descending order. The result of the model is a maximization of the cumulative capture of each factor as NIINs are added to the list in prioritized order.

The cumulative capture of various metrics is compared between the WNO model approach and various other modeling approaches. Other model approaches include ranking NIINs based on requisition and whiskey requisition volumes, requisition volume, criticality score, dollar usage, and randomly. Random NIIN rankings produced incredibly poor results. The other models performed better than WNO in one or two measures, but much worse than WNO in others. From an across-the-board holistic perspective, WNO significantly outperformed all other models.

Unlike each of the other models, WNO encourages tighter controls on factors strongly affecting fill rate, operational readiness, budget and lead time. Focusing on each of these factors rather than just one or two of them identifies and attacks the root of what eventually becomes a lower fill rate metric. For instance, high variance in lead times or requisition volume contributes to extremely poor inventory level predictability. Focusing item manager and contract specialist attention on these underlying issues could account for and/or stabilize the variance, leading to higher fill rates. Another example considers dollar usage. Shelved inventory represents inventory budget that is unavailable for the purchase of other items. If the shelved inventory is extremely expensive, the tradeoff for holding it is the inability to purchase many more less expensive inventory items. The WNO model does not focus on meeting immediate demand; it focuses on identifying the important and problematic items under management.

The time frames of requisition data used to rank NIINs are 24 months for requisitions and 12 months for whiskey requisitions. These decisions were made by WSS managers based on experience, previous analysis, and subject matter expertise. Sensitivity analysis is conducted on alternate time frames ranging from 36 months down to 6 months. The analysis shows that cumulative metric capture changes very little as the time frames change. Therefore, re-prioritizing NIINs every 6-12 months based on 24 months of requisition and 12 months of whiskey requisition data is a suitable approach for the model.

In an effort to compare and contrast different models, numerous single- and multiple-criteria prioritization models are also employed to rank NIINs. Specific emphasis is placed on comparing the WNO model with the ABCD model, a model based solely on requisition and casualty report volume that is currently being implemented by WSS. To test the predictive ability of WNO, particularly in comparison with the ABCD model, requisition data for a recent 3-month time frame is analyzed. The results show that more than 500 requisitions were categorized higher by the WNO model than the ABCD model. 200 of them were categorized in the top two WNO categories (out of 4) versus the lowest ABCD category (out of 4). Additionally, the fill rates for those requisitions were significantly lower than the WSS fill rate average. This analysis is very

limited in scope, as it covers such a short time frame, but the results are in line with the theory behind using more than just requisition volume to prioritize NIINs.

Any of the models introduced, analyzed, and compared are far superior to the historically employed first-in, first-out process. Still, of all the models explored, the WNO model certainly provides the best holistic approach for NIIN prioritization. The value provided by the model would affect numerous aspects of NIIN management and ultimately provide significant benefits to WSS metrics and the operational readiness of the U.S. Naval Forces.

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Duffuaa, S., Raouf, A., & Campbell, J. D. (1999). *Planning and control of maintenance systems: Modeling and analysis*. New York: John Wiley & Sons.

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I. INTRODUCTION

A. BACKGROUND

The Naval Supply Systems Command (NAVSUP) Weapons System Support (WSS) branch is responsible for the parts support of naval maritime and aviation weapon systems. This support includes numerous aspects such as procurement, production, repair, and transportation. WSS's responsibility is uniquely complex relative to other private sector businesses due to the size of its inventory (more than 400 thousand parts) and its multi-item, multi-indenture, multi-echelon (MIME) system. The two specific components making the system MIME are parts repair and the numerous distribution centers. Specifically, depot level repairable (DLR) items are not only issued to customers by WSS, but also are received back from customers when they become inoperable. WSS contracts a repair order on that part so that it can be repaired and placed back into WSS inventory to fulfill a future customer's request.

Each part in the Navy supply system is identified by its own unique National Item Identification Number (NIIN). NIIN inventory support consists of two primary processes, planning and contracting. The projected naval supply needs for each NIIN must be individually analyzed and planned (both long-term and short-term) by WSS planners. Once the NIIN support plan is determined, contracting specialists work to have that NIIN placed on production and/or repair contracts. These processes vary with every NIIN, based on vendor, weapon system, budget, and numerous other variables. Additionally, the NIIN plans and contracts must be periodically reviewed and updated to reflect attribute changes.

Consider an example involving a DLR cooling pump required for a weapon system installed on numerous warships. A WSS item manager is assigned to manage the support for that pump. Suppose the item manager notices that demand has suddenly increased for the pump and concludes that the initial group of procured and installed pumps is starting to reach the end of its life cycle. Knowing that it will not be long before additional pumps fail, the item manager plans for a demand spike by requesting an

increase in procurement and/or repair contracts for the pump. That request is transmitted to contracting specialists who then obligate funds to contract the repair of inoperable pumps and/or procurement of new pumps. The ready-for-issue (RFI) pumps would then be sent to a supply depot to replenish the pump inventory in anticipation of the demand spike forecasted by the item manager.

Planners and contractors currently process all NIIN requirements primarily via a first-in, first-out (FIFO) system. In uncommon cases where there are immediate fleet readiness issues, fleet supply officers contact WSS to specifically request that NIINs be prioritized based on immediate mission needs and worked as soon as possible. This process is applied to all NIINs across the board, regardless of NIIN attributes. The current system does not necessarily allocate WSS's limited resources, such as contracting specialist time and budget, to the items most important to fleet readiness. The suboptimal resource allocation leads to less-than-ideal WSS performance metrics such as fill rate (available stock to fill initial order), average delay days (time it takes WSS to release material for shipment), backorders (unfilled orders awaiting fulfillment), logistics response time (time between customer requisition and delivery), and so on. Perhaps fleet readiness, WSS's primary goal, might be higher with a more objective resource allocation process.

In an effort to increase fill rate, WSS is in the process of implementing a four-band "ABCD" inventory classification system for its maritime inventory. The goal of this system is to prioritize and focus WSS resources on NIINs in the highest demand band (A), which would minimize or eliminate the unfilled orders on those items. Limiting the missed fills on those high-demand items would give WSS the largest fill rate "bang for the buck" resource allocation. The system looks solely at demand, casualty reports (CASREPs), and platform readiness drivers to group NIINs into the four categorical bands. CASREPs are requisitions for parts required to fix a system critical to the ship's assigned mission. Platform readiness drivers are NIINs identified by planners to be very problematic, either from a mission readiness perspective or a supply chain perspective. No other NIIN attributes are considered in this classification scheme. The classification category thresholds are determined by managers based on what they deem a

manageable workload within each group. WSS introduced this system in November of 2013 and has been slowly implementing the system into its maritime inventory management process over the first few quarters of 2014.

Table 1 describes the proposed ABCD criteria for inventory classification established by WSS managers. Criteria that govern this process consider NIIN requisitions over the past 24 months and NIIN CASREP requirements over the past 12 months. For instance, a NIIN must have a minimum of 55 requisitions or nine CASREPS to be classified as an "A" NIIN. Additionally, there were approximately 30 items moved to the B category from the C/D categories due to specific platform-degrading qualities. The number of WSS-managed maritime NIINs that fall into each category is also listed.

Classification	Requisitions(24 months) / CASREP(12 months)	NIINs
A	≥ 55 or ≥ 9	673
B	≥ 27 & ≤ 9	747
C	≥ 13 & ≤ 9	1,489
D	≤ 12 & ≤ 9	137,976

Table 1. Classification levels are set via historical 24-month demand data, 12-month CASREP data, and specified platform degraders.

While this ABCD method introduces at least some sort of prioritization scheme, there are many more factors that surely influence fleet readiness and WSS effectiveness. This thesis explores alternative modeling techniques and factors that may provide more value to WSS and the naval fleet than just fill rate. For instance, over 1 billion dollars has been spent by WSS to repair and procure parts over the past 24 months. A model that considers only requisitions and CASREPs may not be the best technique for improving efficiencies associated with WSS budget allocation. Small improvements in efficiency might equate to hundreds of millions of dollars in savings and/or significant readiness improvements.

B. ABC ANALYSIS

The ABCD method, as well as each of the methods we explore, is derived from Always Better Control (ABC) analysis. ABC analysis, also known as selective inventory control, is an inventory categorization technique used to classify and prioritize stock items for different levels of management attention (Dickie, 1951, p. 1). The analysis is based on Pareto's law, which states that the significant items in a group usually constitute only a small portion of the total number of items in that group (Duffuaa, Raouf, & Campbell, 1999, p. 198). The law can be applied to many fields of study, and is particularly applicable to inventory management. ABC uses dollar usage, the product of demand volume and unit price, as its primary metric (Collier and Evans, 2010, p. 221). This reasoning is due to the fact that there are a finite number of dollars available for inventory, and those dollars must be used wisely. Dollar usage is preferable to using solely volume or price because a high volume of low-price items or a low volume of high-price items may not necessarily require high inventory investment or strict controls. Figure 1 demonstrates a typical "70-20-10" breakdown of an inventory's percent dollar value versus percentage of inventory items.

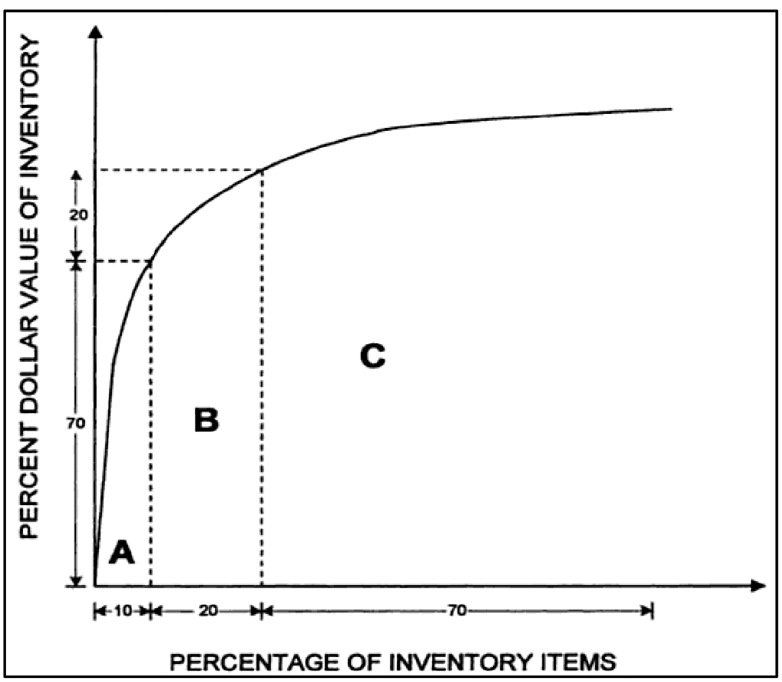

Figure 1. Pareto Diagram (from Duffuaa, Raouf, & Campbell, 1999, p. 198).

Because large inventories can be extremely difficult and expensive to manage optimally, the ABC classification gives managers a way to prioritize business resources. The "A" items are considered to be the major business drivers, accounting for a large portion of the sales. They should be allocated ample resources and assigned tight controls in an effort to maximize efficiencies in meeting demand. The "B" group is approximately twice as large as the "A" group, equates to only about a third of the "A" group's business, and requires looser controls. All other items make up the "C" group. This group typically consists of 70% of all inventory items and is responsible for a trivial portion of the business. Because there is very little return on the investment, resources should be allocated to "C" items only as required. By focusing on the business drivers, the ABC method allows businesses to significantly increase return on capital by lowering inventory costs and minimizing stock-out rates.

Original ABC analysis is the first of many inventory control techniques currently employed throughout the corporate world. Each method focuses on a different metric, and its applicability varies from business to business. Table 2 displays a few of the early alternative ABC methods and their respective focus measures. A few of the measures for these methods are subjective in nature and can be difficult to both implement and update as conditions change.

<table>
<tr><th>Type</th><th>Definition</th><th>Measures</th></tr>
<tr><td>ABC</td><td>Always Better Control</td><td>Annual consumption on value</td></tr>
<tr><td>XYZ</td><td>N/A</td><td>Value of inventory undertaken during the closing of annual accounts</td></tr>
<tr><td>HML</td><td>High-Medium-Low Value</td><td>Unit value of the item</td></tr>
<tr><td>FSN</td><td>Fast-Slow-Non Movement</td><td>Stock rotation, identifies obsolescence</td></tr>
<tr><td>VEIN</td><td>Vital-Essential-Important-Normal Criticality</td><td rowspan="2">Performance, guarantee, warranty, reliability, safety, maintainability, functional utility, criticality, etc.</td></tr>
<tr><td>VED</td><td>Vital-Essential-Desirable Criticality</td></tr>
<tr><td>GOLF</td><td>Government-controlled, Ordinarily available in market, Locally available and Foreign imported purchase</td><td rowspan="3">Availability, lead-time (converting indent to order, manufacturing, transportation, inspection). (LLT/SLT)</td></tr>
<tr><td>SDE</td><td>Scarce item or Single source item, Difficult or Easy to obtain</td></tr>
<tr><td>SOS</td><td>Seasonal & Off-seasonal</td></tr>
</table>

Table 2. Descriptions of ABC-derived inventory management techniques (from Gopalakrishnan, 2002, p. 165).

With business models varying greatly across industries, these ABC models have been adopted and tailored to fit specific situations. Additionally, as business models have evolved and computing power has strengthened, more complex multi-criteria inventory models have been developed and improved. Regardless of the model most applicable to a particular business, Pareto's law and the ABC classification model remain the underlying principles behind most inventory management techniques in use today. In the case of WSS's resource allocation, numerous ABC model variants and their applicability to the WSS NIIN dataset are explored in an effort to determine the most appropriate fit.

C. THESIS PURPOSE

The purpose of this thesis is to determine the most applicable and effective modeling approach to prioritize the large number of NIINs under WSS control. Various ABC methods are researched and analyzed in an effort to understand their potential applicability to the WSS business processes. WSS inventory item and sales document data are studied and analyzed to determine the factors most important to operational readiness and fill rate. Based on those factors, the best ABC model can be selected and tailored to WSS inventory management needs. Once the model is built, it will be used to prioritize WSS NIINs for resource allocation.

The model results are compared and contrasted with alternative prioritization methods, including the ABCD method currently being implemented by WSS. The models will be compared using inventory attributes and metrics determined to have a significant impact on WSS's primary goal, fleet readiness. This thesis also explores what types of fleet readiness improvements could be expected through the implementation of an ABC classification system. The data used in this thesis was provided by Navy Weapons Systems Support.

II. LITERATURE REVIEW

A. ABC MODEL VARIANTS

Pareto's law is the original theory behind the ABC inventory management technique. Over time, newer and better methods have been developed. "XYZ," "HML," "FSN," "VEIN," "VED," "GOLF," "SDE," and "SOS" are all early 1-dimensional evolutions from "ABC" analysis. Over the past 20 years, newer and more advanced multi-criteria inventory classification (MCIC) variations have been developed. These methods have evolved from 1-dimensional models to 2-dimensional multi-criteria models to multi-dimensional models, utilizing modern computing capabilities. Every model aims to achieve the same goal of prioritizing items either on a categorical or individual basis. Eight specific multi-dimensional models will be explored in detail so that their applicability to WSS business requirements can be properly assessed. These variants include joint-criteria matrix, MUSIC-3D, operations-related groups, analytic hierarchy process, genetic algorithm for multi-criteria inventory classification, weighted linear optimization, simple classifiers for multiple-criteria ABC analysis, and weighted non-linear optimization models.

1. Joint-Criteria Matrix

One of the first MCIC models was introduced by Flores and Whybark (1987). The model uses two criteria to create a joint-criteria matrix. Figure 2 shows how dollar usage can be combined with criticality to create a 3x3, nine-category classification matrix. Criticality refers to the potential cost incurred from being unable to fulfill an order. An example of a stock-out cost could be the likelihood of losing a customer's future business to another supplier. The opportunity cost of losing that customer could be much higher than just the revenue loss of a single sale. For the example in Figure 2, category "AA" represents the highest priority category (highest dollar usage and criticality) and "CC" represents the lowest priority category (lowest dollar usage and criticality). Items not directly falling on one of the diagonal categories ("AA", "BB", or "CC") are subjectively moved to the diagonal category best representing their priority.

The arrows in the matrix represent a possible move for the off-diagonal items. For instance, item 1 contains a dollar usage class of "B" and a criticality class of "A". The arrow shows that the decision maker subjectively chose to place the item in "AA" instead of "BB" based on reasons such as specific item characteristics or category sizes. With some subjective decision-making, the MCIC methodology works well for 2 criteria. Unfortunately, the process becomes very complicated as the number of criteria increases.

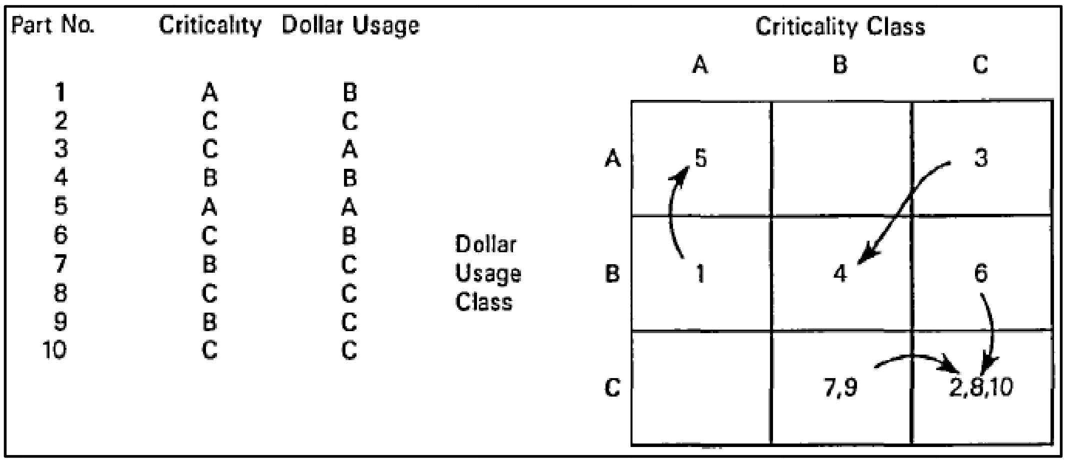

Figure 2. Joint Criteria Matrix (from Flores and Whybark, 1987, p. 41).

2. MUSIC-3D

Gopalakrishnan introduced the MUSIC-3D model as a combination matrix focusing on three dimensions: finance, operations, and materials (Gopalakrishnan, 2002, p. 167). The matrix is composed of cells differentiating items by "Critical/Non-critical (C/NC)" versus "High/Low consumption value (HCV/LCV)" and "Long/Short Lead Time (LLT/SLT)." Figure 3 shows how inventory items are categorized according to MUSIC-3D. In the example, each number represents the categorical priority of that particular cell. For instance, category 1 (highest priority) contains critical parts with high consumption values and high lead times. Category 4 (medium priority) contains non-critical parts with high consumption values and slow lead times. Category 8 (lowest priority) contains non-critical parts with low consumption values and short lead times. This approach is generally applicable to many business models because its focus areas are typically the three most important inventory control factors. A major downfall of this

model is the subjective ranking of each category. For instance, ranking the “HCV-SLT-NC” parts higher than the “LCV-LLT-C” parts is an extremely important decision that could significantly impact business performance and success.

	HCV		LCV	
Critical	LLT 1	SLT 2	LLT 5	SLT 6
Non-critical	3	4	7	8

Figure 3. MUSIC-3D matrix (from Gopalakrishnan, 2002, p. 167).

3. Operations-related Groups

Cohen and Ernst (1988) introduced operations-related groups (ORG) as another MCIC method. The ORG method clusters inventory items based on a number of statistical clustering procedures and operational constraints such as physical and technical descriptors, market attributes, production- and distribution-related parameters, and financial data (Cohen and Ernst, 1988, p. 7). The goal of ORG is to minimize the performance issues resulting from shortfalls in a small number of outlier items. For instance, consider a situation where a particular system requires five different parts that fit numerous systems and are all supplied by different manufacturers. A long lead time experienced by just one part could severely limit an otherwise timely order fulfillment. ORG focuses on managing clusters of parts in a way that minimizes these types of order fulfillment issues.

4. Analytic Hierarchy Process

Flores, Olson, and Dorai (1992) applied Saaty’s (1977) Analytic Hierarchy Process (AHP) to inventory as yet another MCIC method. The AHP arranges the elements of a complex and unstructured situation into a hierarchy of nodes with branches (Saaty, 1977, p. 258). Relative importance measures are subjectively applied by decision makers and then synthesized by AHP, using pairwise comparisons, to provide value measures (Saaty, 1977, p. 258). In the case of inventory management, AHP assigns relative weights to specified item criteria. These weights are then used to create and

assign scores to inventory items. Items are ranked in priority order based on their scores. Figure 4 demonstrates the initial structure of AHP applied to inventory categorization. Three criteria make up "criticality," while four criteria, including "criticality," make up "utility." Figure 5 displays a "relative importance" scale that could be used to assign values to the criteria. The scale ranges from 1 through 9 with 1 representing equal importance between factors and 9 representing maximum difference in importance. Figure 6 displays a sample matrix of criteria with relative and subjectively assigned scalar values. If the row criterion has higher value than the corresponding column criterion, the integer scalar value is used. If the column criterion is higher, the reciprocal value is applied to that particular cell. For instance, the importance of "avg unit cost" is 1/8th of the "criticality" importance. Figure 7 shows the resulting formula from the eigenvalues of the matrix. Scores for each item are calculated using this formula, and then the items are ranked, by score, in order of priority.

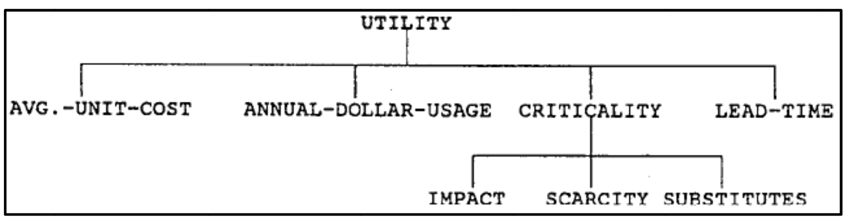

Figure 4. AHP Structure (from Flores, Olson, & Dorai, 1992, p. 74).

Scale	Relative Importance	Explanation
1	Equal importance	Both factors contribute equally
3	Weak preference	The base factor is slightly more important than the second factor
5	Essential preference	Base factor strongly preferred
7	Demonstrable preference	Definite preference for base factor
9	Absolute preference	Base factor preferred at highest possible level

Figure 5. Relative importance scale used for value assignments (from Flores, Olson, & Dorai, 1992, p. 74).

	AVG UNIT COST	ANNUAL DOLLAR USAGE	CRITICALITY	LEAD TIME
AVG UNIT COST	1	1	1/8	1/4
ANNUAL DOLLAR USAGE		1	1/3	1/6
CRITICALITY			1	1
LEAD TIME				1

Figure 6. Pairwise comparison matrix (from Flores, Olson, & Dorai, p. 74).

0.07872 AVG UNIT COST + 0.09161 ANNUAL DOLLAR USAGE
+ 0.41969 CRITICALITY + 0.40999 LEAD TIME (Inconsistency Index = 0.044).

Figure 7. Resulting formula from AHP process (from Flores, Olson, & Dorai, 1992, p. 74).

5. Genetic Algorithm for Multi-Criteria Inventory Classification

Artificial Neural Networks (ANN) and Genetic Algorithm for Multi-criteria Inventory Classification (GAMIC) use genetic algorithms to build upon the AHP method. They aim to alleviate a few of the assumptions and restrictions of AHP. These assumptions include the measuring units of criteria, independence of the decision-maker's subjective scale assignments across all criteria, and consistency of the decision-maker's comparisons (Guvenir and Erel, 1998, p. 31). Unlike the AHP method, these methods are also able to detect and extract nonlinear relationships and interactions among predictor variables (Partovi and Anandarajan, 2002, p. 391). GAMIC relaxes these three assumptions by using a sample of classified items to assign criteria weights.

Consider an example where there are four item criteria, three priority classes (A, B, C), and 150 items. A decision-maker subjectively assigns 10 items to each of the three classes. Data analysis software, such as R with the "ANN" package, then scans the data for patterns and converges on the optimal weights for each criterion so as to maximize the similarity among grouped items and maximize the dissimilarity between the three groups. The optimal weights are then assigned to the variables of the remaining 120 items and the items are classified accordingly. This machine learning method learns from a "model" sample and creates a weighted optimization formula without the decision-

maker's subjective criteria scale assignments required by AHP. It also is unaffected by different weights and scales among each criterion.

Figure 8 provides a visual sample of the process, composed of three layers making up an ANN. The model is provided with input variables and output classifications for each observation in the training dataset. These values make up the input and output layers. The model then iterates through numerous weight combinations of observation inputs to create the hidden layer units (input weights). The converged-upon hidden layer unit values represent the best weighting of input variables to predict each of the item classes. The input variables of new observations can then be entered into the model and classified as one of the three classes based on the training set weight values.

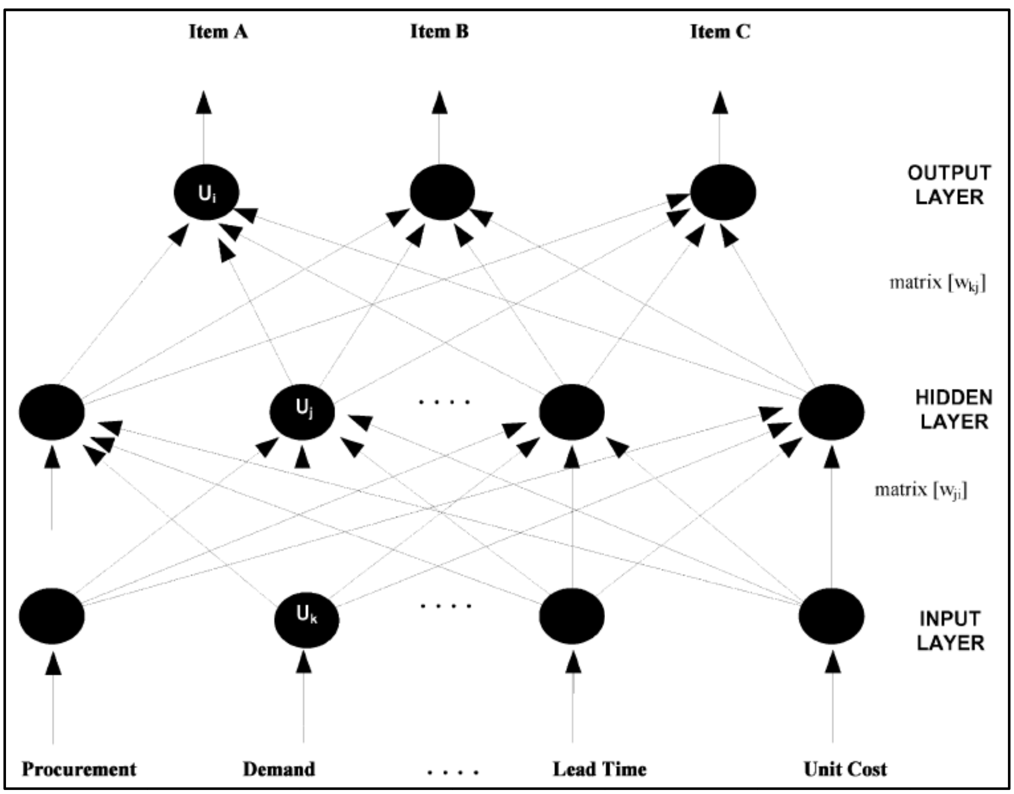

Figure 8. Sample structure of an ANN
(from Partovi & Anandarajan, 2002, p. 392).

6. Weighted Linear Optimization

Weighted linear optimization (WLO) is an ABC analysis approach introduced by Ramanathan (2006). In this approach, a weighted additive function is used to aggregate the performance of an inventory item, in terms of different criteria, to a single optimal inventory score (Ramanathan, 2006, p. 696). Items are then prioritized and grouped based on those scores. Figure 9 shows the formulation for the model. In this particular formula, there are *N* inventory items with measured performance in terms of *J* criteria. The performance of the m^{th} inventory item for each criterion is denoted y_{mj}, which is assumed to be positively related with the importance level of the item. The weight assigned to *j* criterion is represented by v_{mj}. The model assigns weights to each variable to maximize the total summed scores among all items being considered. The model maximizes metric volume capture among all variables, regardless of relative variable importance.

$$
\begin{aligned}
\max \quad & \sum_{j=1}^{J} v_{mj} y_{mj}, \\
& \sum_{j=1}^{J} v_{mj} y_{nj} \leqslant 1, \quad n = 1, 2, \ldots, N, \\
& v_{mj} \geqslant 0, \quad j = 1, 2, \ldots, J.
\end{aligned}
$$

Figure 9. Weighted linear optimization formula (from Ramanathan, 2006, p. 697).

7. Simple Classifier for Multiple-criteria ABC Analysis

To eliminate the requirement for optimization software while also providing comparable results, Ng (2007) introduced a simple classifier for multiple-criteria ABC analysis (SCMD). Like WLO, this model converts all criteria measures of the inventory items into a scalar score. The Ng model differs from WLO in a few significant ways. First, the criteria measures are transformed to a comparable base. The formula used for this transformation is shown in Figure 10. The criterion measure of each item (y_{ij}) is compared with the maximum (max_i) and minimum (min_i) measures for that criterion across all items. Weights are then assigned to the criteria using a combination of

subjective priority rankings, partial averages, and optimization. This technique requires the decision-maker to prioritize the criteria, but individual weights are not assigned subjectively or by optimization software. Once the transformations are applied and criteria are ranked, partial average scores are calculated for each criterion of each item. The highest variable score for that item, also known as the "maximal" score, becomes that item's identifying score and is used to rank it among the group. In the SCMC formulation shown in Figure 11, S_i, j, w_{ij}, and y_{ij} represent item i's maximal score, criterion, the weight assigned to that criterion, and transformed criterion value, respectively. Figure 12 displays the process summary for determining an item's total summed score, which is used to rank it within the universe of inventory items.

$$\frac{y_{ij} - \min_{i=1,2,\ldots,I}\{y_{ij}\}}{\max_{i=1,2,\ldots,I}\{y_{ij}\} - \min_{i=1,2,\ldots,I}\{y_{ij}\}}$$

Figure 10. SCMC criteria transformation formula (from Ng, 2007, p. 345).

$$\begin{aligned}
\max \quad & S_i = \sum_{j=1}^{J} w_{ij} y_{ij} \\
\text{s.t.} \quad & \sum_{j=1}^{J} w_{ij} = 1, \\
& w_{ij} - w_{i(j+1)} \geqslant 0, \quad j = 1,2,\ldots,(J-1), \\
& w_{ij} \geqslant 0, \quad j = 1,2,\ldots,J
\end{aligned}$$

Figure 11. SCMC formulation, post-transformation (from Ng, 2007, p. 346).

Step 1. Calculate all partial averages, $\frac{1}{j}\sum_{k=1}^{j} x_{ik}$, $j = 1,2,\ldots,J$.
Step 2. Compare and locate the maximum among these partial averages. The corresponding value is the score S_i of the ith item.
Step 3. Sort the scores S_i's in the descending order.
Step 4. Group the inventory items by principle of ABC analysis.

Figure 12. SCMC process, post-transformation (from Ng, 2007, p. 348).

8. Weighted Non-linear Optimization

Improving upon SCMC, Hadi-Vencheh (2010) proposed a simple weighted non-linear optimization model (WNO) that combines the positive qualities from both SCMC and WLO. Like SCMC, WNO requires transformation of the criteria to a comparable

base. As the formulation in Figure 13 shows, WNO assigns a weighted aggregate score to each item based on a simple optimization problem consisting of nonlinear constraints. As with the SCMC formulation, S_i, j, w_j, and y_{ij} represent item i's total summed score, criterion, the weight assigned to that criterion, and transformed criterion value, respectively. Weights are assigned to each criterion with an objective of maximizing the total sum of scores over all items. The constraints for WNO differ from both the SCMC and WLO models. This model uses squared weights as opposed to linear weights. Utilizing squared weights expands the feasible region, leading to more precise scoring. Weight constraints based on a subjective priority ranking of the criteria restrict a lower priority attribute from being weighted higher than a higher-priority attribute. Lastly, the sum of squared weights must equal 1. Once optimal weights are assigned, item scores are calculated and the items are then ranked in descending order based on those scores. Partitions for "ABC" groupings can be made at any points based on preferred group sizes.

$$\begin{aligned}
\max \quad & S_i = \sum_{j=1}^{J} y_{ij} w_j, \\
\text{s.t.} \quad & \sum_{j=1}^{J} w_j^2 = 1, \\
& w_j \geqslant w_{j+1} \geqslant 0, \quad j = 1, 2, \ldots, J-1, \\
& w_j \geqslant 0, \quad j = 1, 2, \ldots, J.
\end{aligned}$$

Figure 13. Simple WNO formulation, post-transformation (from Hadi-Vencheh, 2010, p. 965).

WNO ultimately proves to be the most applicable model to the NIIN prioritization goals of WSS. Of all the models discussed, it is the only one that can create an optimal prioritized list based on any number of items, variables, and variable priority rankings. Additionally, though the model is simple enough to run without advanced optimization software, it is also flexible enough to add and change constraints and factors as needed. Thus, the remainder of this thesis focuses on applying the WNO methodology to WSS's inventory.

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III. DATA AND METHODOLOGY

A. SCOPE

NAVSUP WSS is responsible for the program and supply support of Naval forces weapons systems. This entails wholesale- and retail-level support for both maritime and aviation weapons systems. For decades prior to March of 2010, the Navy used a combination of legacy systems to provide parts support to the fleet. The introduction of a new Enterprise Resource Planning (ERP) system in 2010 provided the Navy with a single system able to monitor and control the Navy's entire inventory. With its implementation, came the ability to track all aspects of parts flow through the Navy's MIME model. The detailed data gives analysts a great ability to identify issues and make significant progressive changes to WSS business rules and inventory practices.

The vast number of systems and components comprising each of the Navy's warships, coupled with the numerous types of active platforms, results in an extremely large number of parts required to keep the fleet operating. Compared to the aviation community where a much larger number of aircraft operate within each platform, intermittent and low demand items are much more prevalent in the maritime community. This leads to much lower predictability and forecasting success, which results in lower fill rate and operational readiness. Fill rate represents the proportion of orders WSS is able to immediately fill with on-hand inventory. Fill rate is an overarching metric that affects, in at least some capacity, all other WSS performance metrics. The maritime forecasting difficulty is a big reason why WSS currently achieves supply fill rates of approximately 70% for maritime operations versus 90% for aviation operations. Due to the greater complexity and higher challenges associated with maritime items, this study will focus only on maritime NIINs.

Time frame is also a major consideration in this analysis. All maritime NIINs with a demand of at least one unit over the three-year period from April 2011 through March 2014 are included in the analysis. NIINs failing to accumulate at least a single demand over that period are assumed to be highly unpredictable, low priority, and a poor

return on investment from a resource-allocation perspective. Because the majority of maritime NIINs are dormant stock with little demand, this constraint places the majority of maritime NIINs in the lowest priority band. Sensitivity analysis is conducted with various time frames in mind, but the demand data and metrics prior to March of 2011 remain excluded from the study.

Another consideration for the study's scope is particular NIIN characteristics. For various reasons, WSS is directed to manage NIINs differently based on predefined mission priorities. In other words, many NIINs have been classified by higher authority to warrant maximum attention, and they will not compete with the majority pool of NIINs for priority resource allocation. Specific examples of exclusions from the pool include parts that are specific to nuclear platforms, the SUBSAFE program, performance based logistics (PBL) contracts, and specific cognizance codes (COG).

Nuclear platforms are considered by the Department of Defense (DOD) to be of the utmost priority. Therefore, parts required specifically to support those platforms will not compete with other parts for resources. SUBSAFE items are those considered vital to the safe operation of submarines. Like nuclear parts, they have the utmost priority and do not compete with other parts for resources. PBL NIINs are items that are under contract to be supplied directly by a commercial logistics provider. These contracts are put in place for numerous reasons that are intended to improve readiness and/or costs. Navy COG codes are two-digit classification codes that identify the type and manager of a NIIN. Though there are more than 180 COG codes used in the supply system, six codes make up the majority of the Navy's inventory. The NIINs classified within this group of six COGs compete with each other for resources. They are the focus of this study, and their details are shown below in Table 3.

Code	Definition	Inventory Manager or Retail Office
1H	Consumable material assigned to NAVICP MECH for inventory management	Naval Inventory Control Point, Philadelphia
3H	NAVICP MECH managed Field Level Repairables	Naval Inventory Control Point, Mechanicsburg, PA
7E	Depot level reparable ordnance equipment, ordnance repair parts and air missile repair parts related to Naval Air Systems Command equipment	Naval Inventory Control Point Mechanicsburg, PA
7G	Depot level reparable electronic material to support Space and Naval Warfare Systems Command	Naval Inventory Control Point Mechanicsburg, PA
7H	Depot level reparable shipboard and base equipment, assemblies, components and repair parts related to Naval Sea Systems command equipment	Naval Inventory Control Point Mechanicsburg, PA
7Z	General purpose electronic test equipment to support various Naval Systems Commands equipment/programs	Naval Inventory Control Point Mechanicsburg, PA

Table 3. Details of the six COGs included in the analysis.

Another consideration for NIIN inclusion in this analysis is the item's maturity. NIINs experience five life-cycle phases: initial operational capability, pre-material support date, demand development interval, mature, and sunset. The majority of items are in the mature life-cycle phase (phase 4), and they are the ones analyzed and prioritized.

Over time, parts change due to a multitude of reasons, including design and/or supplier changes. When a change takes place, the updated parts are identified by new NIINs. Most of the time, updated and old parts remain interchangeable and can be substituted for each other. In this case, the NIINs are assigned to a family code that identifies them as being interchangeable. Within the family, the primary NIIN is considered the family "head," while each of the others is considered a family "member." In this analysis, demand for the entire family is summed and applied to the family head NIIN. The characteristics associated with the family head NIIN are the ones applied to that family.

In summary, the scope of this analysis includes WSS-managed maritime NIINs with a demand of at least one over the specified three-year time frame. Nuclear, SUBSAFE, PBL, and specified cognizance items will be excluded. Only items in the mature phase of their lifecycle will be analyzed. Of the 272,000 maritime NIINs, 140,885 of them meet the Nuclear, SUBSAFE, COG, PBL, and lifecycle constraints. When considering a demand history of at least 1 in the past three years and the family

associations, the number of NIINs used in the analysis is just 17,587. These are the NIINs analyzed and ultimately prioritized by the model.

B. DATA

The NIIN details available via ERP reports include more than 70 different attributes pertaining to the more than 400,000 parts in the Navy's supply system. The availability, accuracy, and units of measure of certain elements vary greatly across the universe of NIINs. These attributes reflect unique qualities of each NIIN, including classification, lead time measures, demand, forecasts, physical characteristics, price, etc. Before addressing the analysis of attribute interrelationships and their correlation to fleet readiness performance measures, a few of the basic overarching data categories and their primary components are discussed. Specifically, these are demand, lead times, repair measures, price, and classifications.

Demand is a category with significant effect on fleet readiness. In terms of ERP features, the category's primary components are demand forecast, demand sigma (deviation), requisition frequency, requisition size, regeneration demand, and attrition demand. Demand forecast is the expected unit demand of an item based on numerous analytical tools, methods, and demand history. As outlined in the Navy ERP's functional design specifications document, the forecasting process uses a six-step method with a system of classifications, checks, and balances to determine and verify the forecasting method most applicable to each NIIN. The process of forecasting demand for an item consists of the following six primary steps:

- Determine unit history pattern
- Perform historical data outlier analysis
- Perform process change analysis
- Perform trend analysis
- Calculate demand forecast and sigma
- Perform statistical process control analysis

Demand sigma is a measure of the demand variability. ERP is able to apply different measures of demand deviation to NIINs based on demand characteristics.

Requisition size and requisition frequency represent the average number of units per order and the number of orders per quarter, respectively. Attrition demand is the portion of demand expected to be fulfilled through the purchase of new material, also known as "new procurement." Regeneration demand is the portion of demand expected to be fulfilled through the repair of recycled assets. The requirement for new procurement of assets could be due to numerous reasons including increased demand, increased repair lead time, decreased repair ability, and asset losses.

Lead time represents the expected delay time associated with particular portions of the supply chain. ERP tracks NIIN-level lead times and sigmas (deviations) for procurement, production, procurement administrative, repair, and repair administrative. Those details are important for setting safety levels and demand forecasts, as well as identifying areas where efficiencies could be improved. Procurement problem variable (PPV) comprises the demand and lead time measures associated with each NIIN. Specifically, NIIN attrition and regeneration demand expectations are combined with their respective lead times to determine a combined demand over lead time value.

The ability to repair certain inventory items saves the Navy millions of dollars each year by way of not completely replacing the assets. These substantial cost savings come at the expense of a much more complex supply chain. ERP's measures of repair ability include forecasts, rates, and sigmas for survival, carcass return, and retrograde pipeline loss. Survival rate represents the probability that a carcass will be repaired successfully by the depot-level repair facility. Carcass return rate represents the probability that carcasses (inoperable units) will be returned to the depot level for repair. Retrograde pipeline loss rate represents the portion of carcasses that will be lost due to repair and non-repair reasons, including survival rate and carcass return rate.

Numerous price types are associated with each NIIN. These include standard, net, replacement, and repair. The different prices reflect a part's ability to be repaired, the price to repair it, and the price to replace it. All Navy parts are classified as either consumable items or DLR items. DLR items are repairable and consumable items are not repairable. The classification is based on whether repairing the item would be more economical than replacing it with a new one. For example, a $10 shower curtain would

be considered a consumable item, whereas a $25,000 pump assembly would be a repairable. Standard and net prices represent incoming revenue for WSS from inventory sales. Replacement and repair prices represent costs due to inventory replenishment. The standard price of an item is charged to the customer for either a consumable part or a repairable part with no carcass turn-in. Net price is the rebate price charged to the customer when a carcass turn-in is provided. Replacement and repair prices are those paid by WSS to repair and replace the inventory items, respectively. As with commercial businesses, the standard and net prices are usually higher than the replace and repair prices due to additional costs of managing the inventory.

Classifications make up the largest portion of ERP's metadata elements. Classes, indicators, codes, identifiers, symbols, routers, and flags comprise approximately half of the total data fields. These elements are used not only to identify the specific managers, locations, and treatments of NIINs, but they are also used in many ERP decision trees that determine the demand forecasts and inventory level settings assigned to the NIINs.

Data availability, consistency, and completeness within ERP vary greatly across the universe of NIINs. The reasons for these issues include ERP inconsistencies, limited item manager time for data updates, and different data feed timing, to name a few. Considering the more than 100 data fields available through the ERP NIIN attribute and sales document data tables, it is not uncommon to find more than a third of those fields empty. The number and types of problem fields vary from NIIN to NIIN. Additionally, the data types and measurements vary greatly from field to field. These types include continuous, categorical, binary, and integer. The vast differences from field to field make popular data analysis techniques extremely difficult, if not impossible.

C. VARIABLE SELECTION

In the effort to prioritize NIINs for resource allocation, there must be an understanding of what NIIN attributes should drive their prioritization. A combination of regression analysis and subject matter expertise provides the best approach to determining the drivers of WSS's primary goals, fill rate and operational readiness. Each method is used to check and balance the other.

The significant differences in unit type, measurement, and magnitude among data elements render typical and popular regression analysis techniques impractical. Attempting to correct the underlying assumptions of uncorrelated errors, constant variance of errors, and linear independence of predictors would be nearly impossible with such a large diverse dataset. Therefore, using traditional regression analysis techniques which operate under these assumptions is not a feasible option.

Instead, a relatively new approach introduced by Breiman (2001) is utilized for the regression analysis. This machine learning ensemble method combines the qualities of advanced clustering analysis with regression analysis to classify observations and/or prioritize factors. Random forests are generated by growing a multitude of decision trees from random data points in a large dataset. A decision tree represents a predictive modeling approach that maps an item's qualities (predictor variables) to its target value (response variable). The leaves of the tree represent specific classes and the branches represent conjunctions of factors that lead to those classes.

A detailed decision tree sample provided by Rokach & Maimon (2008) is shown in Figure 14. In this example, the tree is used to facilitate the underwriting process of mortgage applicants. The variables considered for determining whether a mortgage application is approved, denied, or manually reviewed are years at current job, loan to value ratio, marital status, years at current address, and number of dependents. For example, if an individual has been at a job for at least two years, is divorced, and has at least one dependent, the decision is to approve the application. If the individual is single instead of divorced, the decision is to disapprove the application.

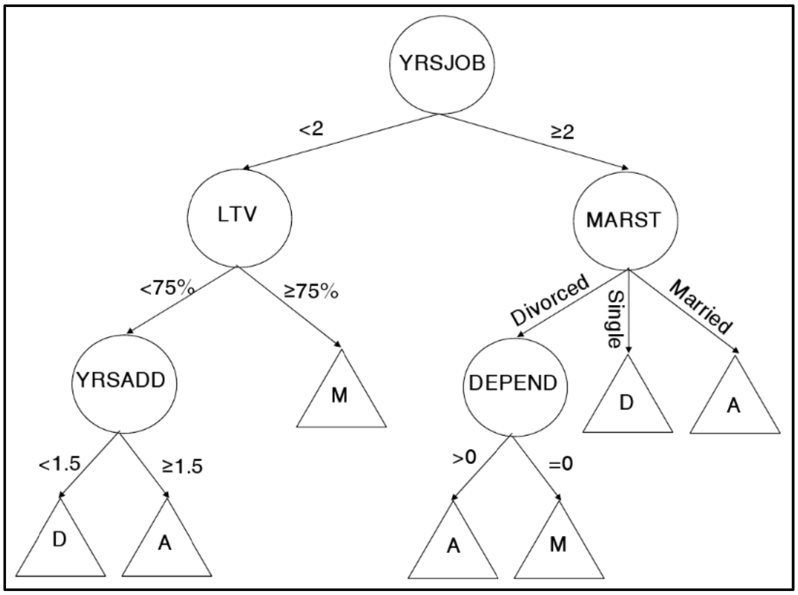


Figure 14. Sample of a decision tree used to facilitate the underwriting process of mortgage applicants (from Rokach & Maimon, 2008, p. 7).

For each tree in a random forest, a subset of random observations is chosen from a full observation set. From those observations, random subsets of predictor variables are selected. Then, an optimal binary split is made on each branch using the variable and its value that best achieve the specified objective function. This process is repeated multiple times, decreasing the mean squared residual error at each split. The final product represents one tree in the forest. Ultimately, the random selections of observations and predictor variables produce an ensemble of independently constructed trees. Once the forest is fully assembled, the node split values are aggregated and used to create classification criteria. Additionally, the variables are ranked against each other based on how often and at what level they were chosen as the node's best binary split variable. Because the objective of this analysis is to identify and verify factors to be considered as fill rate drivers, the relative ranking of variables is the primary goal of the random forest. The chart in Figure 15 provides a brief overview of the process used in building a random forest.

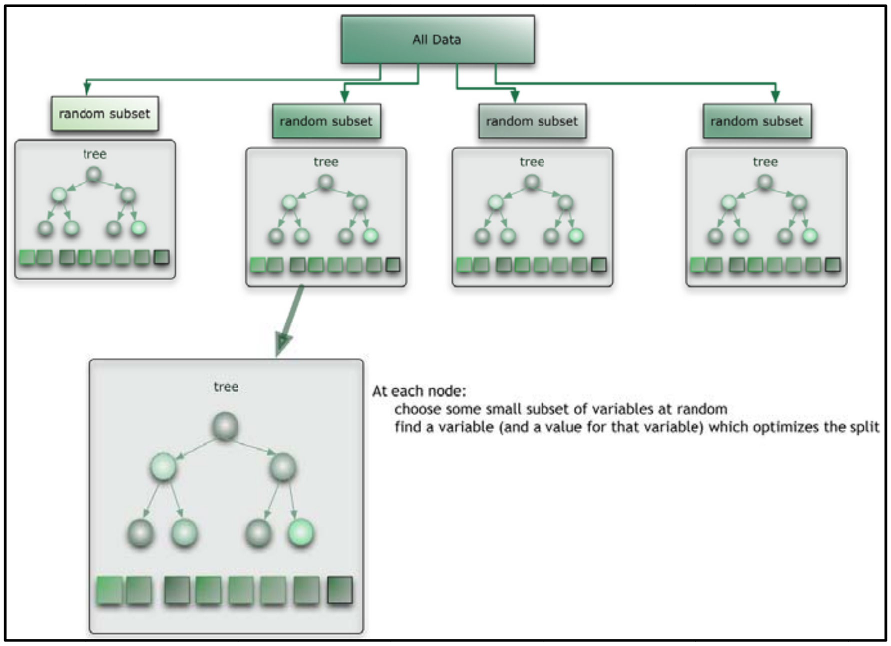


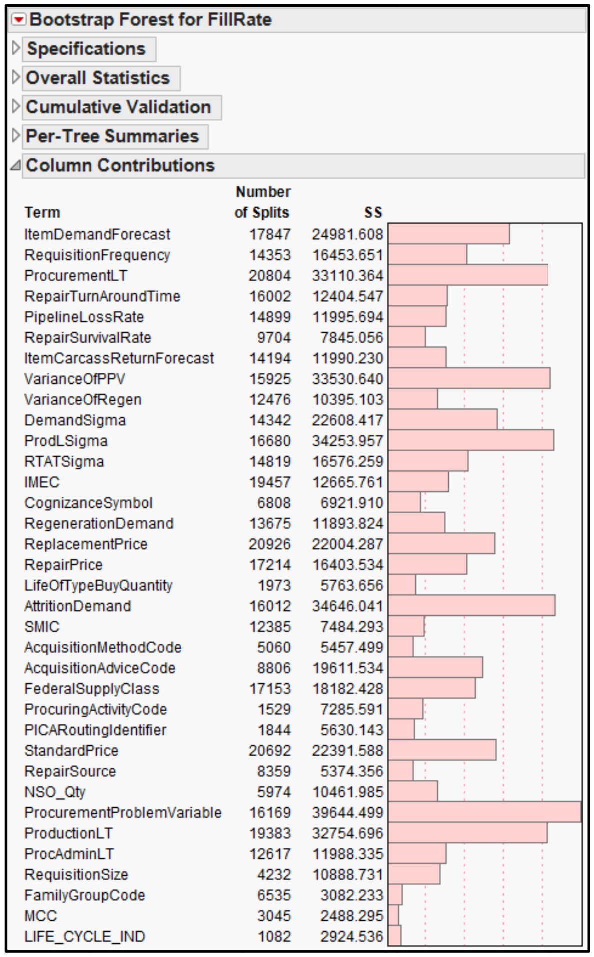
Figure 15. Random forest construction (from Benyamin, 2012).

For this analysis, JMP version 10, a statistical software product provided by SAS is used. Random forests of 1,000 trees are constructed for the full observation set of 17,587 NIINs competing for priority assignment. All available data (the 70+ fields) are included and act as the predictor variables. Additionally, fill rate for every NIIN (drawn from compiled sales document data) is used as the response variable. Therefore, the objective for tree construction is to minimize the error in predicting the fill rate. Fill rate is chosen as the response variable because it directly affects the majority of other WSS metrics, and is the primary metric of concern for WSS. Other metrics such as backorders, average delay days and logistics response time are not analyzed because fill rate correlates highly with each of them. Additionally, NIIN attributes such as PPV and lead times aren't considered as response variables because they are directly calculated by a combination of other NIIN attributes.

The strategy of using all available data to begin the process results in a much more comprehensive outcome, but requires a bit more manual work and time. The first few random forest builds identify variables that overpower the majority of other variables due to extremely high correlation with fill rate. For example, fill rate is a direct reflection

of its primary driver, on-hand inventory. If a requisition is received and there is inventory immediately available to fill it, the requisition earns a “hit”. Every requisition will either count as a “hit” or “miss” towards fill rate based on whether inventory is on hand or not. Because we already know that on-hand inventory will directly affect fill rate, including it as a predictor variable is unhelpful. Additionally, its correlation with fill rate is so high that it dwarfs the random forest results of other variables. As these overpowering variables are identified, they must be manually removed from the dataset and excluded in successive forest builds. Once all of the overpowering variables are removed, the variables that account for very few splits can also be removed.

Common sense, item manager advice, and WSS analyst advice are used in double-checking that the random forest suggestions are correct before any variables are removed. This iterative process is basically a sequence of removing the variables that are insignificant to the goals of this study so that the relative importance among remaining variables can be more appreciated. After much iteration, the final results are shown in Figure 16. The size of the pink bar for each variable represents that variable’s relative strength in explaining fill rate. For instance, the pink bar associated with PPV is the largest in the table, meaning it is the most important variable in the effort to explain fill rate. The results in the table, coupled with subject matter expert verification, primarily point to the variables associated with measures of and/or variance in demand, time, price, and criticality. These factors are the ones further discussed and included in the prioritization model.



Bootstrap Forest for FillRate

Specifications

Overall Statistics

Cumulative Validation

Per-Tree Summaries

Column Contributions

Term	Number of Splits	SS
ItemDemandForecast	17847	24981.608
RequisitionFrequency	14353	16453.651
ProcurementLT	20804	33110.364
RepairTurnAroundTime	16002	12404.547
PipelineLossRate	14899	11995.694
RepairSurvivalRate	9704	7845.056
ItemCarcassReturnForecast	14194	11990.230
VarianceOfPPV	15925	33530.640
VarianceOfRegen	12476	10395.103
DemandSigma	14342	22608.417
ProdLSigma	16680	34253.957
RTATSigma	14819	16576.259
IMEC	19457	12665.761
CognizanceSymbol	6808	6921.910
RegenerationDemand	13675	11893.824
ReplacementPrice	20926	22004.287
RepairPrice	17214	16403.534
LifeOfTypeBuyQuantity	1973	5763.656
AttritionDemand	16012	34646.041
SMIC	12385	7484.293
AcquisitionMethodCode	5060	5457.499
AcquisitionAdviceCode	8806	19611.534
FederalSupplyClass	17153	18182.428
ProcuringActivityCode	1529	7285.591
PICARoutingIdentifier	1844	5630.143
StandardPrice	20692	22391.588
RepairSource	8359	5374.356
NSO_Qty	5974	10461.985
ProcurementProblemVariable	16169	39644.499
ProductionLT	19383	32754.696
ProcAdminLT	12617	11988.335
RequisitionSize	4232	10888.731
FamilyGroupCode	6535	3082.233
MCC	3045	2488.295
LIFE_CYCLE_IND	1082	2924.536

Figure 16. Random forest results for growth of 1000 trees with fill rate as response and wholesale file metadata.

D. VARIABLE ANALYSIS

The response variable, predictor variables identified by the random forest model, and predictor variables identified by subject matter experts are all further analyzed to determine their applicability and contribution to a prioritization model. Specific categories to be analyzed include fill rate, demand, lead time, criticality, and price. Each category includes numerous attributes and each of them is individually considered as a model contributor.

1. Fill Rate

Fill rate, the response variable, is a measure of the proportion of requisitions immediately filled with on-hand inventory. Fill rate is the primary performance measure for WSS because it directly affects all other customer-oriented performance (such as average delay days, backorders, logistics response time, etc.). The fill rate for a NIIN is calculated by averaging the hit/miss binary values for NIIN requisitions over a specific time frame. The chart in Figure 17 displays the 36-month fill rate summary statistics for the 17,587 NIINs included in this analysis. The quartiles show that 25% of the NIINs had a fill rate of 100% and 25% of the NIINs had a fill rate below 20%. The mean fill rate for the entire group was 62.13%. This is substantially lower than the WSS maritime goal of 85%.

Fill Rate (%)		
Quartiles	100%	1.00
	90%	1.00
	75%	1.00
	50%	0.78
	25%	0.20
	10%	0.00
	0%	0.00
Stats	Mean	0.62
	Std Dev	0.41

Figure 17. Fill Rate Distribution among full set of NIINs for the time period April 2011 through March 2014.

2. Demand

Numerous variables are associated with NIIN requisition and demand values. The requisitions table on the left-hand side of Figure 18 displays the 36-month requisition total summary statistics for the collection of NIINs. The values range from 1 to 4871, with a mean of 13.64. With an upper quartile value of just 10, it is clear that a small portion of NIINs make up a large portion of requisitions. This is a prime example of the basic concept of ABC analysis. The table on the right-hand side of Figure 18 provides summary statistics for the average requisition size by NIIN. Non-integer values are due

to the fact that some NIINs have unique units of issue and can be requisitioned in non-integer values. Though the maximum quantity ordered was nearly 550, lower and upper quartile values of 1 show that the vast majority of requisitions are for a single unit. Additionally, more than 10% of the NIINs contain a requisition size of 0, which is due to one of two reasons; either the ERP data for a NIIN is not updated or ERP's requisitions size for that NIIN is correct, but that NIIN is a family head NIIN and its members are the ones with actual requisitions.

Requisitions		
Quartiles	100%	4871.00
	90%	27.00
	75%	10.00
	50%	3.00
	25%	1.00
	10%	1.00
	0%	1.00
Stats	Mean	13.64
	Std Dev	72.60

Requisition Size		
Quartiles	100%	547.76
	90%	1.47
	75%	1.00
	50%	1.00
	25%	1.00
	10%	0.00
	0%	0.00
Stats	Mean	1.99
	Std Dev	11.07

Figure 18. Summary statistics for 36-month requisition totals and requisition sizes for each NIIN.

The Navy's repair program is a system of refurbishing used assets and then reissuing them for further use. In most cases, expensive parts are able to be repaired at a much lower cost than completely replacing them. Repair survival rate and repair pipeline loss rate (RPLR) measure the reparability of a particular NIIN. Repair survival rate represents the portion of assets that experience a repair attempt and is able to be repaired. The repair survival rate table in Figure 19 shows a median repair survival rate of .9, which means that only 10% of total repair attempts fail. RPLR represents the portion of assets lost in the repair pipeline and unable to be issued again. These reasons include, but are not limited to, surveys (lost by customer), lost in transit, and beyond economical repair. The pipeline loss rate table shows a median RPLR of .13, which means that only 13% of all repair assets are unable to be issued at least one more time.

Repair Survival Rate		
Quartiles	100%	1.00
	90%	1.00
	75%	0.92
	50%	0.90
	25%	0.01
	10%	0.00
	0%	0.00
Stats	Mean	0.67
	Std Dev	0.41

Pipeline Loss Rate		
Quartiles	100%	1.00
	90%	1.00
	75%	0.99
	50%	0.13
	25%	0.09
	10%	0.03
	0%	0.01
Stats	Mean	0.35
	Std Dev	0.40

Figure 19. Summary statistics for repair survival rate and repair pipeline loss rate.

Unlike requisitions, which only consider orders for an item regardless of the quantity requested for each order, quantity demand represents the total volume of items requisitioned. For instance, 20 separate requisitions for a particular NIIN could all be for different quantities of that NIIN. The quantity demand of that NIIN would be the sum of those quantities, whereas the requisitions of that NIIN would number just 20. Quantity demand of a NIIN will always be at least as high as the number of requisitions for that NIIN.

The majority of attributes analyzed pertain to unit demand, not requisitions. Specific demand measures include quantity demand, demand sigma, regeneration demand, and attrition demand. Figure 20 displays the summary statistics for each of these attributes. The 36-month quantity demand values correspond to the requisition and requisition size statistics. A maximum quantity demand of 40,567 and an upper quartile of just 12 show how low the demand is on the majority of NIINs. The demand sigma statistics directly reflect the difficulty in predicting the demand for such low-demand items. This difficulty is displayed via a median sigma of .5 on a median demand of just 4. Though coefficient of variation would be a better measure of relative variance, demand sigma is tracked by ERP and easier to obtain and use by WSS analysts. Therefore, the ERP sigma measures are used throughout this analysis.

Regeneration demand represents the portion of demand expected to be met through repair. In contrast to regeneration demand, attrition demand represents the portion of demand expected to be met via new procurement (purchase of new items).

These values play a large role in budget expectations due to the much higher price associated with purchasing new items. They also reflect how well a repair pipeline may be or should be operating.

Quantity Demand		
Quartiles	100%	40567.00
	90%	39.00
	75%	12.00
	50%	4.00
	25%	2.00
	10%	1.00
	0%	0.00
Stats	Mean	38.41
	Std Dev	486.11

Demand Sigma		
Quartiles	100%	2167.77
	90%	2.85
	75%	1.14
	50%	0.51
	25%	0.22
	10%	0.00
	0%	0.00
Stats	Mean	3.51
	Std Dev	37.23

Regeneration Demand		
Quartiles	100%	1646.76
	90%	2.49
	75%	0.82
	50%	0.24
	25%	0.00
	10%	0.00
	0%	0.00
Stats	Mean	1.46
	Std Dev	15.56

Attrition Demand		
Quartiles	100%	15423.00
	90%	2.63
	75%	0.48
	50%	0.12
	25%	0.03
	10%	0.00
	0%	0.00
Stats	Mean	8.78
	Std Dev	165.86

Figure 20. Summary statistics for 36-month quantity demand, demand sigma, regeneration demand, and attrition demand.

3. Lead Time

Lead times represent the time duration of specific processes in the supply chain. These processes include contracting, new procurement production, and repair production. The random forest identified four lead time measures as strong fill rate drivers. They are procurement administrative, production, procurement, and repair turnaround lead times. Procurement administrative lead time represents the number of days it takes to award a procurement contract to a supplier. The clock starts when the contracting office receives a purchase request from an item manager, and ends when the contract is awarded. At that point, the production lead time clock starts. Production lead time measures the number of days it takes the supplier to manufacture and deliver the purchase order. Procurement lead time is the sum of the procurement administrative and production lead times. As opposed to the case of production lead time, repair turnaround time represents the time required to repair and deliver a repair order.

As can be seen in Figure 21, the median lead times (measured in days) for each of the processes are relatively low. The primary issue to highlight from these statistics is that the variances among lead times are extremely high. Procurement administrative, production, procurement, and repair turnaround lead time measures have standard deviations of 18, 36, 48, and 12 for their respective median measures of just 1, 3, 4, and

2. These statistics point to the fact that there is a relatively small group of NIINs that experience extreme lead time delays. Additionally, these delays exist across all stages in the supply chain, and are not unique to any one or two particular lead time measures.

Procurement Admin LT		
Quartiles	100%	240.00
	90%	1.64
	75%	1.04
	50%	1.04
	25%	0.99
	10%	0.82
	0%	0.00
Stats	Mean	4.73
	Std Dev	17.92

Production LT		
Quartiles	100%	894.25
	90%	6.30
	75%	4.00
	50%	2.83
	25%	1.70
	10%	0.70
	0%	0.00
Stats	Mean	8.84
	Std Dev	35.85

Procurement LT		
Quartiles	100%	984.25
	90%	7.39
	75%	5.20
	50%	3.97
	25%	2.74
	10%	1.74
	0%	0.30
Stats	Mean	13.57
	Std Dev	48.18

Repair TurnAround Time		
Quartiles	100%	461.73
	90%	3.35
	75%	2.41
	50%	1.74
	25%	0.88
	10%	0.00
	0%	0.00
Stats	Mean	2.53
	Std Dev	11.79

Figure 21. Summary statistics for procurement administrative lead time, production lead time, procurement lead time, and repair turnaround time.

Procurement problem variable (PPV) is one of the best indicators of supply chain health for a particular NIIN. It represents demand over lead time. The calculation of PPV shown below considers attrition demand, regeneration demand, procurement lead time, repair pipeline loss rate, and repair turnaround time.

$$\mathrm{PPV} = \begin{bmatrix} \left(\text{Demand over Procurement Lead Time Duration * Repair Pipeline Loss Rate}\right) + \\ \left(\text{Demand over Process Repair Turnaround Time Duration * (1 - Repair Pipeline Loss Rate)}\right) \end{bmatrix} \quad (1)$$

PPV identifies potential issues in the supply chain resulting from higher-than-forecasted demand and/or longer-than-expected lead times. Careful attention to PPV and quick action by item managers can prevent upcoming order fulfillment problems that could lower fill rates. Figure 22 provides summary statistics for PPV and PPV variance. Once again, the majority of high PPV and PPV variance values are accounted for by a small portion of NIINs.

Procurement Problem Var		
Quartiles	100%	15423.00
	90%	6.73
	75%	1.89
	50%	0.63
	25%	0.21
	10%	0.82
	0%	0.00
Stats	Mean	10.24
	Std Dev	166.69

PPV Variance		
Quartiles	100%	6.80E+07
	90%	31.39
	75%	4.46
	50%	0.88
	25%	0.21
	10%	0.00
	0%	0.00
Stats	Mean	8977.81
	Std Dev	539085.25

Figure 22. Summary statistics for PPV and PPV variance.

4. Criticality

Unlike commercial businesses that operate with goals of high revenue, margins, and profit, the Navy supply system must operate with different goals in mind. The notion of criticality and importance must play a major role in NIIN management. Though a high level of demand for a NIIN indicates that it is frequently needed, the criticality of that NIIN could range from insignificant to operationally vital. For instance, consider two types of light bulbs, type A and type B. Type A has an annual demand of 50,000 units because it fits the light socket above every sailor's rack (bed) on every U.S. Carrier. Without the bulb, a sailor would need to utilize another light source for reading. Bulb type B has a demand of just 5 per year, but is a unique specialized bulb that fits a particular electronics panel in every pilothouse in the naval fleet. Without an operating bulb, the electronics panel vital to a vessel's safe navigation is out of commission. Though both types are important, bulb type B is critical to the operational effectiveness of naval forces and should be much more carefully managed than bulb type A. This idea of criticality is typical of military operations and must be strongly considered when prioritizing NIINs for resource allocation.

The three types of criticality measures used for this analysis include whiskey requisitions, requisition priorities, and item management essentiality codes (IMEC). Each individual requisition for a part from WSS contains customer-generated elements that give amplifying information about the order. If a system required for a command to complete an assigned mission becomes inoperable, it is reported as a casualty (CASREP).

The parts required to make that system operable are requisitioned and assigned a "w" (whiskey) requisition number. The whiskey identifies the requisitioned part as preventing a ship from achieving its mission. Approximately 7% of the total requisitions for the NIINs analyzed were classified as whiskey requisitions. For the summary statistics shown in Figure 23, all sales documents during the 36-month period were compiled and the whiskey requisitions were summarized for every NIIN and/or family. Only 25% of all NIINs experienced at least 1 whiskey requisition over the 36-month time period. Further, only 10% experienced 4 or more whiskey requisitions.

The summary statistics in the center column of Figure 23 show that 10% of the NIINs have a whiskey requisition rate (portion of requisitions that are whiskeys) of more than 66.67%. The rightmost column shows that the mean fill rate for NIINs with whiskey requisitions is 75.04%. These figures highlight the fact that a small portion of NIINs account for a large portion of the whiskey requisitions. An additional note is that high-whiskey NIINs achieve a lower fill rate than the low-whiskey NIINs.

Whiskey Requisitions		
Quartiles	100%	548.00
	90%	4.00
	75%	1.00
	50%	0.00
	25%	0.00
	10%	0.00
	0%	0.00
Stats	Mean	1.82
	Std Dev	7.06

% Whiskey Requisitions		
Quartiles	100%	1.00
	90%	0.67
	75%	0.29
	50%	0.00
	25%	0.00
	10%	0.00
	0%	0.00
Stats	Mean	0.18
	Std Dev	0.30

Whiskey Fill Rate (%)		
Quartiles	100%	1.00
	90%	1.00
	75%	1.00
	50%	1.00
	25%	0.50
	10%	0.00
	0%	0.00
Stats	Mean	0.75
	Std Dev	0.39

Figure 23. Summary statistics for 36-month whiskey requisitions, percentage of NIIN requisitions that were a whiskey, and the fill rate for whiskey requisitions.

Each requisition also contains a priority code. This code identifies the command's current operational status and its need for the part. The matrix used to determine the specific priority code is shown in Table 4. The force activity designator (FAD) represents a command's operational state and tasking. FAD priority increases

from left to right, and urgency of need designator decreases from top to bottom. The priority designator values decrease in importance. For example, an inoperable primary radar system (required for the assigned mission) on a deployed Destroyer (FAD I or II, depending on assignment) would warrant a priority designator of 01 or 02. NAVSUP publication 485 volume 1 identifies the criteria required for different FAD and urgency of need designator levels. For this analysis, priority designators 01-03 are considered high priority identifiers.

Figure 24 provides 36-month summary statistics for high-priority requisition volume and the proportion of requisitions for each NIIN that are high priority. As with the whiskey requisition statistics, the majority of NIINs experienced less than two high-priority requisitions. Additionally, a small portion of the NIINs accounted for a large portion of the high-priority requisitions. Lastly, all of the requisitions for 25% of the NIINs were high priority, and none of the requisitions for 25% of the NIINs were high priority.

TABLE RELATING F/AD AND UNDs TO PRIORITY DESIGNATORS

Urgency of Need Designator		FAD I	II	III	IV	V
		Priority Designator				
A	Unable to Perform	01	02	03	07	08
B	Performance Impaired	04	05	06	09	10
C	Routine	11	12	13	14	15

Table 4. Requisition Priority Matrix (from NAVSUP P-485 vol. 1).

High Priority Requisitions		
Quartiles	100%	3669.00
	90%	15.00
	75%	5.00
	50%	1.00
	25%	0.00
	10%	0.00
	0%	0.00
Stats	Mean	7.63
	Std Dev	46.40

% High Priority Requisitions		
Quartiles	100%	1.00
	90%	1.00
	75%	1.00
	50%	0.50
	25%	0.00
	10%	0.00
	0%	0.00
Stats	Mean	0.49
	Std Dev	0.39

Figure 24. Summary statistics for 36-month High-Priority (Pri 1-3) requisitions and proportion of requisitions for each NIIN that are High Priority.

The final criticality measure considered in this analysis is the IMEC. IMECs are assigned to parts based on a combination of military essentiality codes (MEC) and mission criticality codes (MCC). MECs are 1-digit codes assigned to parts based on their essentiality to an applicable end item. They are assigned during the initial provisioning process of parts. MCCs are 1-digit codes assigned to a part based on its criticality to the mission of the military unit where it is installed. MCCs were created and designed to be updated over time in an effort to reflect how often and at what level parts are whiskey-requisitioned.

IMECs are assigned to parts based on a combination of MCCs and MECs. IMEC codes range from 0 through 5, with higher codes representing increased criticality assignment. An IMEC code of 0 is assigned when a part first enters the supply system, and updates as requisition data is obtained. An IMEC code of 5 is reserved for aviation parts and represents parts with the highest criticality assignments. IMEC code assignment is an important concept that can help identify high-priority parts. Unfortunately, many system issues prevent them from being updated regularly and correctly. These issues must remain in mind when factoring criticality codes into the NIIN prioritization model. Figure 25 provides the distribution of IMECs across the dataset. Though this dataset only includes maritime NIINs, 18 NIINs are identified as IMEC code 5 items. This error, coupled with that fact that code 4 is assigned more than any other code, are clear indicators of the inconsistency and updating issues previously mentioned. For the purposes of this analysis, the IMEC codes are assumed to be close enough to the true criticality measures to add value to the model.

IMEC		
Quartiles	100%	5.00
	90%	4.00
	75%	4.00
	50%	3.00
	25%	1.00
	10%	1.00
	0%	0.00
Stats	Mean	2.81
	Std Dev	1.23

Figure 25. Summary statistics for NIIN Item Management Essentiality Codes.

5. Price

Numerous prices are associated with each NIIN. Four price types correspond to the potential revenue and inventory replenishment cost associated with each order. Standard price represents the worst-case scenario for the customer. If a customer is unable to place a carcass back into the pipeline for possible repair and reissue, the standard price is charged for that order. On the other hand, if the customer is able to place the carcass back into the pipeline, the net price is charged. The incoming revenue for that order would be added back to the WSS inventory budget and used for further inventory replenishment, based on inventory needs. As WSS determines what inventory to replenish, it must decide between repairing and replacing assets. WSS is either charged the repair price attached to an asset for the repair decision or the replacement price for the replace (new procurement) decision. The tables in Figure 26 show the large range of prices among the group of NIINs for each price type.

Standard Price		
Quartiles	100%	6504171.00
	90%	40465.60
	75%	15942.00
	50%	5460.00
	25%	1585.00
	10%	290.78
	0%	0.00
Stats	Mean	21397.84
	Std Dev	108117.87

Net Price		
Quartiles	100%	1171258.00
	90%	12977.20
	75%	5269.00
	50%	1549.00
	25%	195.00
	10%	0.00
	0%	0.00
Stats	Mean	6746.44
	Std Dev	26446.76

Replacement Price		
Quartiles	100%	5131600.00
	90%	31145.80
	75%	12308.40
	50%	4260.00
	25%	1229.00
	10%	209.64
	0%	0.00
Stats	Mean	16507.56
	Std Dev	83219.19

Repair Price		
Quartiles	100%	898926.00
	90%	9772.55
	75%	3982.00
	50%	1187.52
	25%	154.14
	10%	0.00
	0%	0.00
Stats	Mean	5018.74
	Std Dev	19621.17

Figure 26. Summary statistics for standard, net, replacement, and repair prices.

To understand the magnitude of differences in pricing, the four price types are studied. Figure 27 provides insight on the pricing differences for net versus standard and repair versus replacement. Of note, all non-repairable items will have $0 listed as their net and repair prices. Though this throws off some of the summary statistics, the median and upper quartile values are unaffected and indicate that the margins are more or less consistent for both comparison tables. The average difference between repair and replacement costs of approximately 32% gives an idea of how much money the Navy is able to save by repairing assets instead of replacing them. The ability to save nearly 32% on hundreds of millions of dollars in parts offers a significant amount of savings for the Navy.

Net vs Standard Price		
Quartiles	100%	3.23
	90%	0.68
	75%	0.42
	50%	0.33
	25%	0.07
	10%	0.00
	0%	0.00
Stats	Mean	0.31
	Std Dev	0.24

Repair vs Replacement Price		
Quartiles	100%	1.46
	90%	0.66
	75%	0.40
	50%	0.32
	25%	0.08
	10%	0.00
	0%	0.00
Stats	Mean	0.30
	Std Dev	0.23

Replacement vs Standard Price		
Quartiles	100%	77.61
	90%	0.79
	75%	0.79
	50%	0.79
	25%	0.79
	10%	0.68
	0%	0.00
Stats	Mean	0.81
	Std Dev	1.39

Repair vs Net Price		
Quartiles	100%	37.89
	90%	0.76
	75%	0.76
	50%	0.76
	25%	0.76
	10%	0.75
	0%	0.00
Stats	Mean	0.77
	Std Dev	0.41

Figure 27. Summary statistics of discount and premium relationships between various price types, including net, standard, repair, and replacement.

The differences in standard versus replacement and net versus repair prices are relatively constant, maintaining a stable 30% margin across the list of NIINs. Overall, the price differences are rather linear on all accounts and the determination for which pricing to include in the model depends on the perspective goals of the model. Revenue (standard or net price), cost (replace or repair price) and margin (standard/net minus replace/repair) are all viable options that must be considered.

WSS uses an optimization program named Service Planning Optimization model (SPO) to determine which NIIN inventories to replenish with the available budget. SPO factors numerous variables into this decision, namely current inventory levels, demand forecast, and price. The higher the budget, the better SPO can perform in meeting demand forecasts. Therefore, consistent budget dollars for inventory replenishment is

extremely important in maintaining the right inventory at optimal levels. Inventory that fails to sell in a timely manner ties up budget dollars, accumulates operating costs, and contributes very little to WSS's primary goal, operational readiness. Dollar usage, the original variable considered in ABC analysis theory, represents this issue and is a primary factor in the prioritization model. Demand, repair pipeline loss rate, and the four types of pricing are all used to calculate expected costs and revenues attached to each NIIN.

6. Summary

Demand, repair ability, lead times, criticality, and price are all primary fill rate drivers and extremely important to WSS's ability to maximize operational readiness. Therefore, they must all be strongly incorporated into any model used to prioritize NIINs for resource allocation and management. Though 21 specific data elements were discussed in this section as fill rate and readiness drivers, they can all be represented through various creative combinations and substitutions of variables. Even so, the categories of variables are different enough that a minimum of at least five or six variables must be utilized. Before determining a model's variables and/or variable combinations, the model to be used for prioritization must be identified.

Revisiting the ABC model options, early ABC models that use just one, two, or three criteria will not suffice for the minimum of five to six variables impacting WSS effectiveness. Additionally, subjectively determining the weights of each variable is extremely difficult when so many variables are critical to operational readiness. Considering the requirements and qualities of each ABC method, only WLO, SCMC, and WNO are potential candidates. Because SCMC significantly improves upon WLO and WNO improves slightly upon SCMC, WNO proves to be the best option for meeting the modeling goals. To reiterate, the major benefits of the WNO model are its ability to run without specialized optimization software, its ability to consider any number of criteria, its variable priority rankings, and the fact that it ranks each NIIN individually instead of by groups.

E. METHODOLOGY AND VARIABLES

Revisiting the details of the WNO methodology, inputs for the WNO model are the NIINs, their chosen ranking criteria, and variable weight constraints (based on subjective variable priority rankings). The criterion for each NIIN is transformed to a score based on its relative ranking among the min-max range for that criterion among all NIINs. The formula for this transformation is shown in Figure 28. These transformations are completed for each criterion of each NIIN. The model then uses these transformed scores in its optimization process. Weights are assigned to each criterion so as to maximize the summed weighted transformed scores across all criteria and all NIINs. The weights for each criterion are constrained to the rankings specified by the decision maker. The sum of weighted criteria becomes the score assigned to each NIIN. Those scores are then used to priority rank the entire list of NIINs. The optimization formula and constraints for WNO are shown in Figure 29. In summary, the WNO model accepts any number of NIINs, any number of variables, and requires only that the decision maker rank each variable in order of importance. The model outputs a prioritized list of NIINs based on capturing the maximum amount of variable value as each NIIN is added.

$$\frac{y_{ij} - \min_{i=1,2,\ldots,I}\{y_{ij}\}}{\max_{i=1,2,\ldots,I}\{y_{ij}\} - \min_{i=1,2,\ldots,I}\{y_{ij}\}}$$

Figure 28. WNO criteria transformation formula (from Ng, 2005, p. 345).

$$\begin{aligned}
\max \quad & S_i = \sum_{j=1}^{J} y_{ij} w_j, \\
\text{s.t.} \quad & \sum_{j=1}^{J} w_j^2 = 1, \\
& w_j \geqslant w_{j+1} \geqslant 0, \quad j = 1,2,\ldots,J-1, \\
& w_j \geqslant 0, \quad j = 1,2,\ldots,J.
\end{aligned}$$

Figure 29. Simple WNO formulation, post-transformation
(from Hadi-Vencheh, 2008, p. 965).

Though the WNO model could theoretically use all 21 of the identified variables, many of these would be redundant and create a much more complex model than required. As with any optimization model, there are numerous tradeoffs with added depth and complexity. In this case, these tradeoffs include significant increases in the model's runtime, increased subjectivity in variable rankings, and less flexibility in adding complexity via NIIN list growth. Ultimately, the goal is to maximize the flexibility and simplicity of the model while capturing as much of the important variable data as possible.

Variables and variable combinations most representative of the fill rate drivers are used in the model. Criticality, dollar usage, requisition volume, requisition variance, PPV, and PPV Variance are the six model variables used to incorporate and represent requisitions, requisitions variance, quantity demand, whiskey requisitions, high-priority requisitions, IMEC-4 NIINs, PPV, PPV variance, RPLR, repair price, and replacement price. Though NIINs with demand of at least 1 over a 36-month period are included in the model, different time frames within that 36-month period are used for the sales document data (requisitions, requisition variance, whiskey requisitions, and high-priority requisitions). All other variables use values provided by the ERP wholesale file tables provided by WSS in May of 2014.

Sales document data covering requisition, requisition variance, and high-priority requisition values over the 24-month period from April 2012 through March 2014 are used in this model. Whiskey requisition data is included for the time frame of April 2013 through March 2014. The two-year requisition and 1-year whiskey requisition time frames were chosen because WSS analysts and decision makers believe those time frames are most representative of future requirements. Any major issues with NIINs prior to those time frames are assumed to have been addressed and worked out by item management processes in place. Additionally, as ERP has steadily become more reliable since its implementation, data collected after the initial transition period tends to be much more consistent. Though the model focuses on the 24- and 12-month time frames, sales document data was gathered and combined for each NIIN over numerous time frames. These alternative time frame figures can be easily implemented into the model for further

study. Table 5 shows an example of the different time frame sales document data values for a single NIIN. The rows represent the total, average, and variance of requisitions, quantity demand, whiskey requisitions, and priority-1 requisitions over five specific time frames. Specifically, these figures over time frames of 36 months, 24 months, 18 months, 12 months, and 6 months were captured.

NIIN	Measure	36tot	36avg	36var	24tot	24avg	24var	18tot	18avg	18var	12tot	12avg	12var	6tot	6avg	6var
000011632	Reqs	30	0.833333	0.638889	21	0.875	0.692708	14	0.777778	0.506173	6	0.5	0.416667	2	0.333333	0.222222
000011632	Demand	30	0.833333	0.638889	21	0.875	0.692708	14	0.777778	0.506173	6	0.5	0.416667	2	0.333333	0.222222
000011632	Whiskey	30	0.833333	0.638889	21	0.875	0.692708	14	0.777778	0.506173	6	0.5	0.416667	2	0.333333	0.222222
000011632	Hi-Pri	22	0.611111	0.515432	16	0.666667	0.555556	12	0.666667	0.555556	5	0.416667	0.409722	1	0.166667	0.138889

Table 5. Demand values for NIIN 000011632 over different time frames.

Requisitions and requisition variance warrant their own individual model variables. Every requisition of a NIIN affects fill rate the same way, regardless of criticality, price, or quantity. Requisition and requisition variance are the best tools to predict and plan for the volume and predictability of future requisitions. This proper planning then leads to requisition fulfillment and increased fill rate metrics. Requisition values for each NIIN over the past 24 months represent a single variable, and the standard deviation of requisition variance over that same time frame will also represent a single variable.

The variable representing criticality is a combination of high-priority requisitions over the past 24 months, whiskey requisitions over the past 12 months, and the NIIN’s assigned IMEC code. The formula used to calculate the criticality score is shown below. The formulation is subjective in nature, but proves to be a good approximation of the importance of each measure to the overall criticality score. In many cases, requisitions will fall under all three measures (whiskey, high-priority, and high IMEC); in which case, that requisition will contribute in three different ways to the NIIN’s criticality measure. In this formulation, whiskey requisitions have a 50% higher weighting than high-priority requisitions and up to multiples of a higher weighting than IMEC. Whiskey requisitions undoubtedly represent the highest priority needs and should be signified as such in any criticality formulation.

$$\text{Criticality Score} = \left[\begin{array}{l}(\text{Whiskey Requisitions} * 1.5) + \text{High-Priority Requisitions} \\ + \text{Total Requisitions} * (.10 * \text{IMEC})\end{array}\right] \quad (2)$$

Table 6 displays how criticality scores would represent a few different scenarios for a single NIIN. Three scenarios were generated for four different NIINs. While IMEC and requisition figures were constant for each NIIN, whiskey and high-priority values were randomly generated for each scenario. The criticality formula was applied to each scenario, criticality scores were generated, and the scenarios were ranked by score. On a relative basis, the rankings for each NIIN under the scenarios make sense and prove to be acceptable measures.

NIIN	IMEC	Requisitions	Whiskeys	High-Pris	Criticality	Rank
1	4	2000	1173	891	3450.5	1
1	4	1000	627	113	1453.5	4
1	4	100	57	1	126.5	8
2	3	2000	1093	912	3151.5	2
2	3	1000	431	175	1121.5	6
2	3	100	51	16	122.5	9
3	2	2000	122	100	683	7
3	2	1000	689	540	1773.5	3
3	2	100	43	34	118.5	10
4	1	2000	606	315	1424	5
4	1	1000	1	1	102.5	11
4	1	100	18	12	49	12

Table 6. Criticality scores and rankings for 4 NIINs under three different scenarios.

As with the requisitions and requisitions variance variables, PPV and PPV variance both warrant their own model variables. They are the only model variables that represent the lead times and potential pipeline problems associated with each NIIN. Specifically, they consider attrition demand, regeneration demand, procurement lead time, repair pipeline loss rate, and repair turnaround time. Of course, many of these factors consider additional measures associated with NIINs. PPV and PPV variance are extremely important to fill rate goals because even if WSS knows exactly what the future demand is going to be, if the parts are not on the shelf due to pipeline issues, the requisition is scored a "miss" and fill rate decreases. PPV and PPV variance values were

drawn for each NIIN from ERP's data tables in April of 2014, and are used as individual variables in the model.

Multiple perspectives must be considered when determining how to factor price into the model. Revenues, costs, and margins all represent different aspects of the business and can be considered for NIIN prioritization. In a non-profit case such as the DOD, margins are not necessarily a real concern. Therefore, revenues or costs, rather than margins, should be the dollar usage driver in the model. Because WSS has more control over spending than it does revenue (over which it has very little), inventory cost proves to be the best pricing basis for the model's dollar usage variable. In summary, the dollar usage variable considers unit demand, retrograde pipeline loss rate, repair price, and replacement price to calculate an expected cost for WSS to supply that unit demand. The formulation used for dollar usage is shown below.

$$\text{Dollar Usage} = \begin{bmatrix} (\text{Retrograde Pipeline Loss Rate} * \text{Unit Demand} * \text{Replacement Price}) \\ + ((1 - \text{Retrograde Pipeline Loss Rate}) * \text{Unit Demand} * \text{Repair Price}) \end{bmatrix} \quad (3)$$

The final step of the WNO model preparation is to rank these six variables (criticality, dollar usage, requisition volume, requisition variance, PPV, and PPV variance) in order of importance. Besides the formulated variables and time frame considerations, this is the only subjective portion of the model setup. Because the model optimizes the variable weights to maximize total summed score, only an ordinal ranking of the six variables is required. All six model variables include at least some form of demand volume. Therefore, the primary fill rate driver (requisitions) will be strongly represented regardless of the variable ranking. With that in mind, focus shifts to variables that encompass other aspects strongly affecting operational readiness.

Criticality represents operational readiness better than all other variables. The fact that just one small part could potentially render an entire warship not operationally ready is reason enough to consider criticality as the highest priority variable. Dollar usage falls in line with the original theory behind ABC analysis. Dollars tied up in stagnant inventory severely diminishes a business's ability to fund high-demand and/or highly critical stock. In this case, stagnant stock not only limits replenishment of high-

demand stock which drives fill rate, but also critical parts that strongly affect operation readiness. WSS's essential need to be as efficient as possible with the limited and constrained budget identifies dollar usage as the No. 2 priority variable.

Requisitions, requisitions variance, PPV, and PPV variance are all heavily correlated with demand. Though PPV and PPV variance can identify potential pipeline problems through lead time measures, higher values aren't necessarily indicative of problems. If inventory levels are set high enough for a high-PPV item, the pipeline may still be very healthy. Still, the item does have the potential to quickly experience major issues if demand or lead times change significantly. On the other hand, higher requisitions and requisitions variance values do directly reflect higher importance to fill rate and operational readiness. Therefore, the initial rankings for the final four variables are requisitions, requisitions variance, PPV, and PPV variance, in order.

In summary, the final variable rankings for initial model runs are criticality, dollar usage, requisitions, requisitions variance, PPV, and PPV variance, in order. Table 7 provides a summary of these variables and the sales document and/or NIIN attributes associated with each variable.

Variable Ranking	Model Variables	ERP / Sales Document Variables
1	Criticality	Whiskey Requisitions, Requisition Priority, IMEC
2	Dollar Usage	Quantity Demand, Repair Pipeline Loss Rate, Replacement Price, Repair Price
3	Requisitions	Requisitions
4	Requisitions Variance	Requisitions
5	PPV	Regeneration Demand, Attrition Demand, Repair Turnaround Time, Procurement Lead Time, Repair Pipeline Loss Rate
6	PPV Variance	Regeneration Demand, Attrition Demand, Repair Turnaround Time, Procurement Lead Time, Repair Pipeline Loss Rate

Table 7. Table of variables and associated attributes that are used to prioritize NIINs in WNO model.

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IV. MODEL ANALYSIS

A. MODEL

One of the major advantages of the weighted non-linear optimization model is its simplicity. The model is designed to be simple enough to run in Microsoft Excel with the basic "solver" add-in and its generalized reduced gradient (GRG) nonlinear solving method. The list of NIINs (17,587) and their six associated variables (criticality, dollar usage, requisitions, requisitions variance, PPV, and PPV variance) are entered into the spreadsheet. Each variable is transformed into a score based on its rank relative to the minimum and maximum values for that particular variable across the entire set of NIINs. For instance, if a particular NIIN has the highest criticality value among the entire group of NIINs, its initial transformed criticality score would be a 1. The next highest NIIN's criticality score would be lower than 1, but the degree to how much lower it is depends on how much lower its criticality variable value is than that of the highest NIIN. The magnitude of differences plays a role in the relative scores for each NIIN. Each transformed score is eventually multiplied by the weight optimally assigned to its particular variable by the solver.

The next step is to rank the variables in terms of importance, which creates constraints for the optimization problem. In the Excel model, the weight of each variable is constrained to being less than or equal to the weight of the next highest variable minus one one-millionth of a point. Each weight is constrained to a non-negative value and the sum of the squared weights for all variables is constrained to a maximum of 1. The weights are squared to increase the feasible region and therefore, supply a more precise result. The squaring will cause the actual weights to sum to more than 1, but this has no negative impact on results or goals.

The weighted transformed variables are summed, creating an individual total score for each NIIN. The final scores for all NIINs are summed to create a total score for the entire list. This total score is the objective function value for the solver's optimization problem. Solver maximizes the total score for the list by optimizing the

weights applied to each transformed variable, subject to the variable ranking and maximum weight constraints. Solver's results represent the optimal weights to capture the highest summed score for the entire NIIN list. Figure 30 provides a sample of the model's constraints. "w" represents the weight applied to each variable, "w+" represents the maximum value that can be used by the next highest priority variable, "w^2" represents w^2 (increases feasible region), "sum" represents the maximum summed "w^2" value, and "Score" represents the model's final summed score across all NIINs.

Metric	w	w+	w^2	sum
Cri	0.491292	0.491291	0.241368	1
DolUse	0.491291	0.49129	0.241367	
Req	0.49129	0.491289	0.241366	Score
Req.SD	0.491289	0.491288	0.241365	109.6629
PPV	0.131407	0.131406	0.017268	
PPV Var	0.131406		0.017268	

Figure 30. Sample of constraints used in the WNO model.

Microsoft Excel 2010's solver add-in with its GRG non-linear solving method is used to solve the optimization problem. A multi-start method with a population size of 250 random starting points (different weights) is specified and used. Convergence and precision values of one ten-billionth of a point are also specified. For the particular example in Figure 30, the optimally generated weights for each metric are approximately 0.4913 for criticality, dollar usage, requisitions, requisitions variance, and approximately 0.1314 for PPV and PPV variance. The maximized score for the model with those specific weights is 109.66.

After the model is run and "Score" is maximized, the NIIN list is ranked by individual summed score to create the prioritized list of NIINs. The rankings are then used to calculate the portion of each metric captured by a specified number of NIINs. For instance, the top 100 ranked NIINs may capture 20% of the entire list's total requisitions. Metric percentage capture presents a clear picture of business drivers and the tradeoffs tied to managing certain NIINs more carefully than others.

B. MODEL RESULTS

Metrics used to measure and compare the model results are based on percentage capture among different groups of NIINs. Table 8 provides the results for different quantities of the top-priority NIINs. The column titles represent the number of NIINs in the grouping, and the row titles represent specific metrics being measured. For instance, the first cell under the "500" title states that the top 500 NIINs account for 40.55% of the total requisitions represented by the entire list of 17,587 NIINs. Continuing down that same column, the same group of 500 NIINs represent 81.99%, 56.42%, 92.64%, 29.28%, 36.56%, 4.86%, and 45.21% of the list's total requisitions variance, PPV, PPV variance, whiskey requisitions, priority 1-3 requisitions, IMEC-4 NIINs, and dollar usage, respectively. Any variety of metrics can be used to measure volume and/or percentage captured by a particular prioritized subset of NIINs, but these best represent the fill rate and operational readiness drivers. Figure 31 provides a visual depiction of the WNO model's metric capture results.

WNO							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	40.55%	47.40%	52.63%	60.30%	66.10%	70.56%	74.03%
Reqs Var	81.99%	85.60%	88.08%	91.00%	92.74%	94.02%	94.95%
PPV	56.42%	63.38%	66.32%	73.80%	78.10%	81.71%	85.37%
PPV Var	92.64%	94.71%	95.74%	97.57%	98.22%	98.75%	99.11%
W	29.28%	36.22%	41.90%	50.81%	57.50%	62.62%	67.42%
HP	36.56%	43.52%	48.62%	56.73%	62.76%	67.49%	71.30%
IMEC-4	4.86%	7.04%	9.27%	13.67%	17.47%	20.99%	24.38%
Dollar Usage	45.21%	51.56%	56.87%	65.04%	71.23%	75.44%	79.17%

Table 8. WNO's results, representing % coverage of total metric value for each specified number of highest priority NIINs.

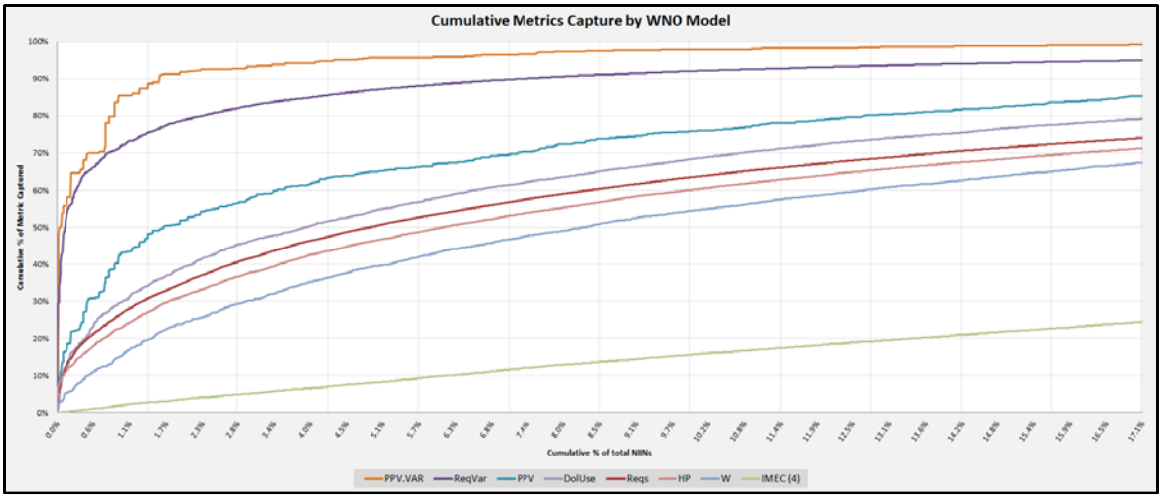

Figure 31. WNO's results, representing % coverage of total metric value for each specified number of highest priority NIINs.

To obtain a better understanding of the value provided by the WNO model relative to other potential prioritization methods, a variety of models are applied to the exact same dataset used to create WNO rankings. Specifically, prioritization schemes based on ABCD criteria, requisition volume, dollar usage, criticality, and uniformity are analyzed. None of these models accurately represent WSS's current FIFO process, but the results of that process would theoretically lie somewhere between those of the random and requisition models.

For the "ABCD" model, NIINs are ranked by category based on the predefined requisitions and whiskey requisition thresholds. For NIINs within the same ABCD category, they are secondarily ranked by requisition volume. NIINs are ranked by requisition volume for the "requisitions" model, by dollar usage for the "dollar usage" model, by criticality score for the "criticality" model, and uniformly for the "random" model.

C. RESULTS OF ALTERNATIVE MODELS

1. ABCD Prioritization

WSS is currently working to implement an ABCD model. The model considers subjectively determined thresholds to categorize NIINs. A reminder of the category

criteria for the model is shown below in Table 9. Category A includes NIINs with greater than 54 requisitions or greater than 9 CASREP requisitions. After ranking the NIINs according to category assignment, the NIINs are ranked within each category based on requisition volume. In its current ABCD method, WSS does not rank items within each classification group. The items were ranked that way in this analysis to represent a best-case scenario (maximizing requisition volume capture) for the ABCD model. Like the results table shown for the WNO model, Table 10 displays the metric capture results for the ABCD model. Though a few of the capture rates are relatively close, others are significantly different. Results are only provided up through 3,000 NIINs because management believes it will be extremely difficult to optimally manage more than 1,000 NIINs, much less 3,000. A ceiling of 3,000 NIINs is used because optimally managing that many is an absolute best-case scenario that will probably never be reached.

Classification	Requisitions(24 months) / CASREP(12 months)
A	≥ 55 or ≥ 9
B	≥ 27 & ≤ 9
C	≥ 13 & ≤ 9
D	≤ 12 & ≤ 9

Table 9. Classification levels are set via historical 24-month demand data, 12-month CASREP data, and specified platform degraders.

ABCD							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	42.27%	48.66%	53.99%	61.82%	67.45%	71.77%	75.22%
Reqs Var	80.19%	84.35%	87.36%	90.59%	92.65%	93.89%	94.92%
PPV	36.49%	48.68%	55.30%	63.06%	73.03%	76.57%	80.72%
PPV Var	62.45%	74.34%	76.43%	81.06%	85.51%	86.66%	90.72%
W	29.48%	39.66%	43.05%	50.05%	55.78%	61.15%	65.26%
HP	36.58%	44.30%	49.03%	56.38%	62.23%	66.83%	70.50%
IMEC-4	5.27%	7.52%	9.64%	13.91%	18.24%	21.92%	25.24%
Dollar Usage	33.78%	40.54%	45.91%	52.37%	58.92%	63.74%	68.05%

Table 10. Results of ABCD prioritization, representing % coverage of total metric value for each specified number of highest priority NIINs.

Table 11 provides a comparison of the WNO and ABCD model results. Each cell represents the increase (green) or decrease (red) in metric capture by using the ABCD model instead of the WNO model. Specifically, the results of the WNO rankings are subtracted from the results of the ABCD ranking, meaning the green cells represent better performance than the WNO model and red cells represent poorer performance than WNO. The top 500 prioritized NIINs in the ABCD model capture 1.73% more requisitions than the WNO model. On the other hand, the ABCD model captures 11.42% less dollar usage than the WNO model. The results show that minor declines in a few metrics using WNO provide significant increases in other categories.

ABCD vs. WNO							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	1.73%	1.27%	1.36%	1.52%	1.35%	1.21%	1.19%
Reqs Var	-1.80%	-1.25%	-0.72%	-0.41%	-0.08%	-0.13%	-0.03%
PPV	-19.93%	-14.70%	-11.02%	-10.75%	-5.07%	-5.14%	-4.65%
PPV Var	-30.19%	-20.37%	-19.31%	-16.51%	-12.71%	-12.09%	-8.39%
W	0.21%	3.44%	1.14%	-0.76%	-1.72%	-1.47%	-2.16%
HP	0.03%	0.78%	0.41%	-0.35%	-0.53%	-0.66%	-0.80%
IMEC-4	0.41%	0.49%	0.37%	0.24%	0.77%	0.94%	0.85%
Dollar Usage	-11.42%	-11.02%	-10.97%	-12.67%	-12.31%	-11.70%	-11.13%

Table 11. Results of NIIN prioritization based on ABCD instead of WNO, representing increase or decrease in % coverage of total metric value for each specified number of highest priority NIINs.

As expected, there exists a high degree of NIIN overlap in the class compositions of both models. This is primarily due to the strong dependence of both models on requisition volume. Based on ABCD parameters applied to the group of 17,587 NIINs, the A, B, and C classes contained 570, 636, and 1,329 NIINs, respectively. Applying those same class sizes to the WNO model's prioritized NIIN list fosters the ability to make an apples-to-apples comparison of classifications. Table 12 displays the classification comparison results. For example, 78.07% of the NIINs classified as "A" by WNO were also classified as "A" by ABCD. Furthermore, 14.91%, 4.21%, and 2.81% of the NIINs classified as "A" by WNO were respectively classified as "B," "C," and "D," by ABCD. Just a slight majority of NIINs for each class were classified the same in both models.

Misclassification Matrix for WNO vs ABCD (% NIIN Overlap)					
		WNO Class			
		A	B	C	D
ABCD Class	A	78.07%	17.77%	0.91%	3.25%
	B	14.91%	56.92%	14.33%	13.84%
	C	4.21%	20.44%	63.84%	11.51%
	D	2.81%	4.87%	20.92%	71.39%

Table 12. Matrix shows the NIIN classification overlap between the WNO and ABCD models, using identical class sizes.

2. Requisitions Volume Prioritization

Ranking NIINs based on requisitions volume is very similar to the ABCD model. The only difference between the two is the consideration of whiskey requisitions. While a full requisition volume approach would aim to solely tackle fill rate, ABCD considers operational readiness. The metric capture differences in prioritizing NIINs strictly by requisition volume instead of the WNO model are shown in Table 13. As expected, the Requisitions model captures a bit more requisition and IMEC-4 volume than WNO, but captures significantly less of the other metrics.

Requisitions vs. WNO							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	1.77%	1.65%	1.53%	1.54%	1.35%	1.21%	1.19%
Reqs Var	-1.56%	-0.97%	-0.79%	-0.42%	-0.24%	-0.17%	-0.08%
PPV	-17.13%	-14.13%	-10.72%	-10.73%	-5.96%	-5.72%	-4.61%
PPV Var	-27.77%	-20.31%	-19.26%	-16.51%	-12.99%	-12.20%	-8.38%
W	-1.64%	-0.85%	-1.82%	-1.38%	-1.68%	-1.61%	-2.21%
HP	-0.56%	-0.47%	-0.49%	-0.43%	-0.57%	-0.73%	-0.83%
IMEC-4	0.51%	0.65%	0.45%	0.14%	0.69%	0.83%	0.87%
Dollar Usage	-12.08%	-10.53%	-11.33%	-11.99%	-12.17%	-11.68%	-11.02%

Table 13. Results of NIIN prioritization based on requisition volume instead of WNO, representing increase or decrease in % coverage of total metric value for each specified number of highest priority NIINs.

3. Dollar Usage Prioritization

Dollar usage, the original metric consideration of ABC analysis is used to prioritize NIINs in the Dollar Usage model. The metric capture differences between the Dollar Usage model and the WNO model are shown in Table 14. Though the dollar usage capture is significantly higher than the other models, the requisitions capture is significantly lower. While the model would promote tighter controls on budget and spending, fill rate could decline significantly with the lower requisition capture.

Dollar Usage vs. WNO							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	-13.46%	-13.88%	-13.83%	-14.18%	-13.29%	-12.93%	-12.03%
Reqs Var	-24.11%	-22.05%	-20.93%	-19.96%	-18.41%	-15.63%	-14.63%
PPV	-24.58%	-27.19%	-26.88%	-28.90%	-25.21%	-23.91%	-23.48%
PPV Var	-19.69%	-17.33%	-17.92%	-17.92%	-13.71%	-11.04%	-9.30%
W	-5.68%	-6.74%	-6.00%	-6.92%	-7.25%	-7.27%	-8.01%
HP	-8.72%	-9.00%	-9.03%	-9.39%	-9.51%	-9.49%	-9.06%
IMEC-4	-1.55%	-2.03%	-2.60%	-3.56%	-4.17%	-4.07%	-3.78%
Dollar Usage	10.18%	10.96%	10.97%	10.33%	9.25%	8.73%	7.78%

Table 14. Results of NIIN prioritization based on dollar usage instead of WNO, representing increase or decrease in % coverage of total metric value for each specified number of highest priority NIINs.

4. Criticality Prioritization

The criticality formula considers requisition volume, whiskey requisitions, high-priority requisitions, and NIIN IMECs. Those considerations arguably make this model the most operational readiness-friendly model of the bunch. Table 15 displays the metric capture differences between prioritizing NIINs based on criticality measure and WNO score. As expected, this model captures a much larger portion of the whiskey requisition, high-priority requisition, and IMEC-4 metrics than the WNO model. Its requisition capture is slightly lower than WNO and the other models, but the potential tradeoff between lower fill rate and higher operational readiness is something to be strongly considered.

Criticality vs. WNO							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	-0.92%	-0.94%	-1.35%	-1.80%	-2.13%	-2.34%	-2.22%
Reqs Var	-6.92%	-5.24%	-5.42%	-5.24%	-4.05%	-3.50%	-3.25%
PPV	-23.39%	-23.79%	-21.79%	-18.57%	-16.95%	-15.18%	-15.15%
PPV Var	-30.26%	-25.37%	-24.32%	-21.10%	-17.49%	-13.24%	-12.73%
W	8.09%	8.55%	9.18%	10.22%	10.45%	11.53%	11.02%
HP	4.04%	4.01%	4.70%	5.12%	4.90%	4.77%	4.78%
IMEC-4	1.10%	1.53%	1.67%	1.26%	1.93%	2.46%	3.23%
Dollar Usage	-10.82%	-10.06%	-10.83%	-12.09%	-13.15%	-13.02%	-12.50%

Table 15. Results of NIIN prioritization based on criticality instead of WNO, representing increase or decrease in % coverage of total metric value for each specified number of highest priority NIINs.

5. Uniform Prioritization

The last model prioritization scheme is based solely on randomness. If no specific prioritization scheme is applied to the full set of NIINs, there should be a relatively linear and steadily increasing correspondence between number of NIINs and percentage of metric captured. For instance, the assumption is made that 10% of the NIINs will account for approximately 10% of each metric. The Random model results are significantly inferior to those of all other models analyzed. Clearly, the terrible

results of this model highlight the importance of applying at least some sort of prioritization scheme to inventory.

Aside from the Random model, all models have specific pros and cons. These pros and cons are amplified as models are compared and contrasted with each other. Graphical depictions of the metric coverage provide a detailed picture of the relative value provided by each model and how that value relates to fill rate and the fleet readiness.

D. COMPARISON OF ALTERNATIVE MODELS

The highest ranked variable in the WNO model is criticality. It is the only variable that applies a sense of operational importance to each NIIN. Figure 32 provides a graphical illustration of the criticality metric captured by each model. The vertical axis represents the cumulative percentage of total criticality captured, relative to the sum of all criticality scores for the entire dataset. The primary horizontal axis (beneath graph) represents the cumulative percentage of total NIINs that captures the corresponding criticality. The secondary horizontal axis (above graph) represents the number of NIINs that make up that cumulative percentage. For example, approximately 60% of the total criticality metric is captured by the top 8% (or 1,400) highest ranked NIINs of the Criticality model. The same number of highest ranked NIINs in the Dollar Usage and Random models captures approximately 45% and 8% of the criticality metric, respectively. Based on the criticality metric, the Criticality model outperforms all models, while the ABCD, Requisitions, and WNO models follow in a close group not too far behind. The Dollar Usage and Random models capture significantly less of the criticality metric than the other models.

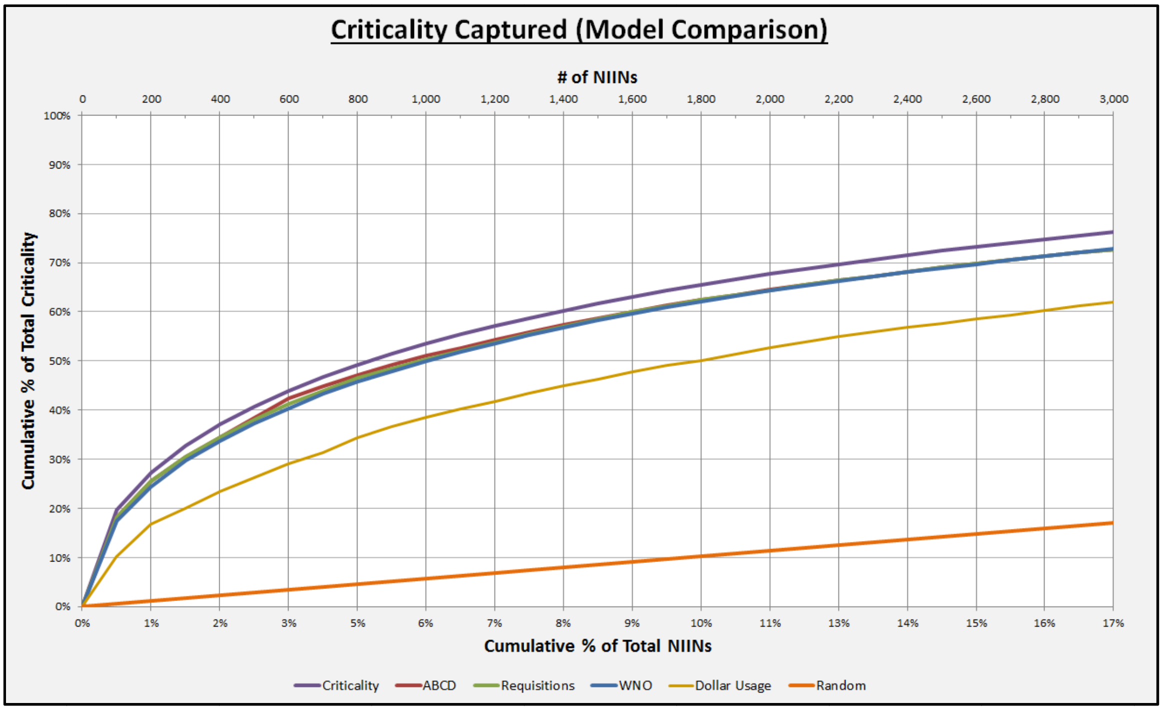

Figure 32. Comparison of cumulative % of total criticality metric captured.

Dollar usage considers requisition volume, cost price, and repair pipeline loss rate. It is important to the efficiency that WSS can exhibit with its inventory budget. Figure 33 depicts how each model performs in terms of dollar usage capture. While the Dollar Usage model outperforms all others, the WNO also significantly outperforms the remaining models. The gaps between models in this chart are some of the largest among all metrics considered.

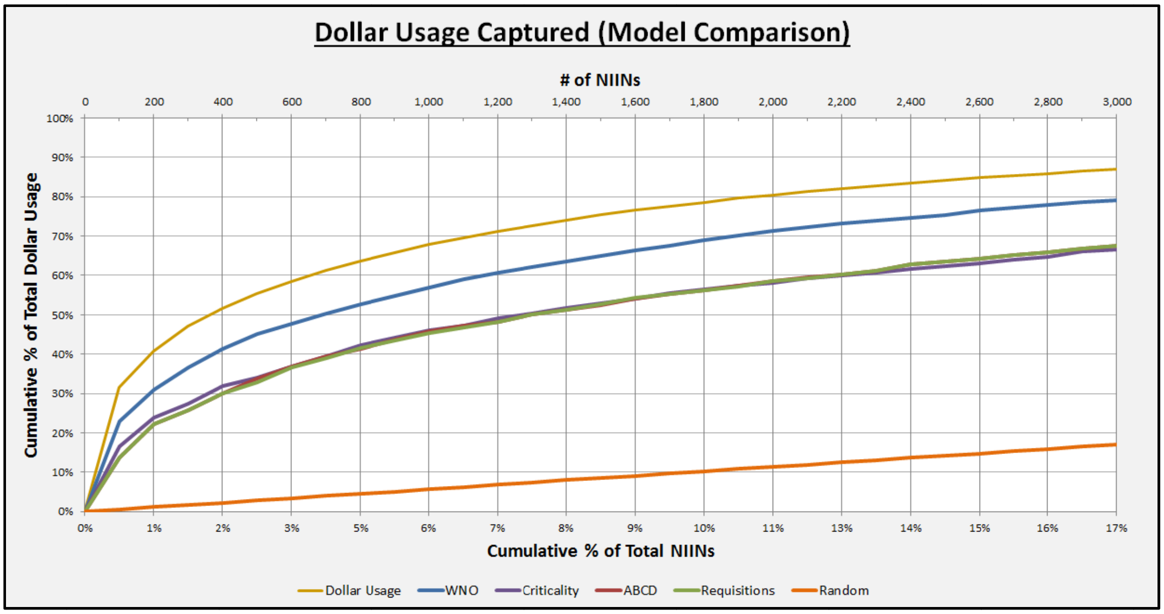

Figure 33. Comparison of cumulative % of total dollar usage captured.

Whiskey requisition metric capture results closely resemble those of criticality score capture. As shown in Figure 34, the Criticality model captures significantly more whiskey requisitions than the other models. The sharp change in the ABCD model line around the 600-NIIN point reflects the ABCD whiskey requisition requirement that is applied only to the category-A NIINs. The WNO, ABCD, and Requisitions models remain tightly grouped as NIINs are added.

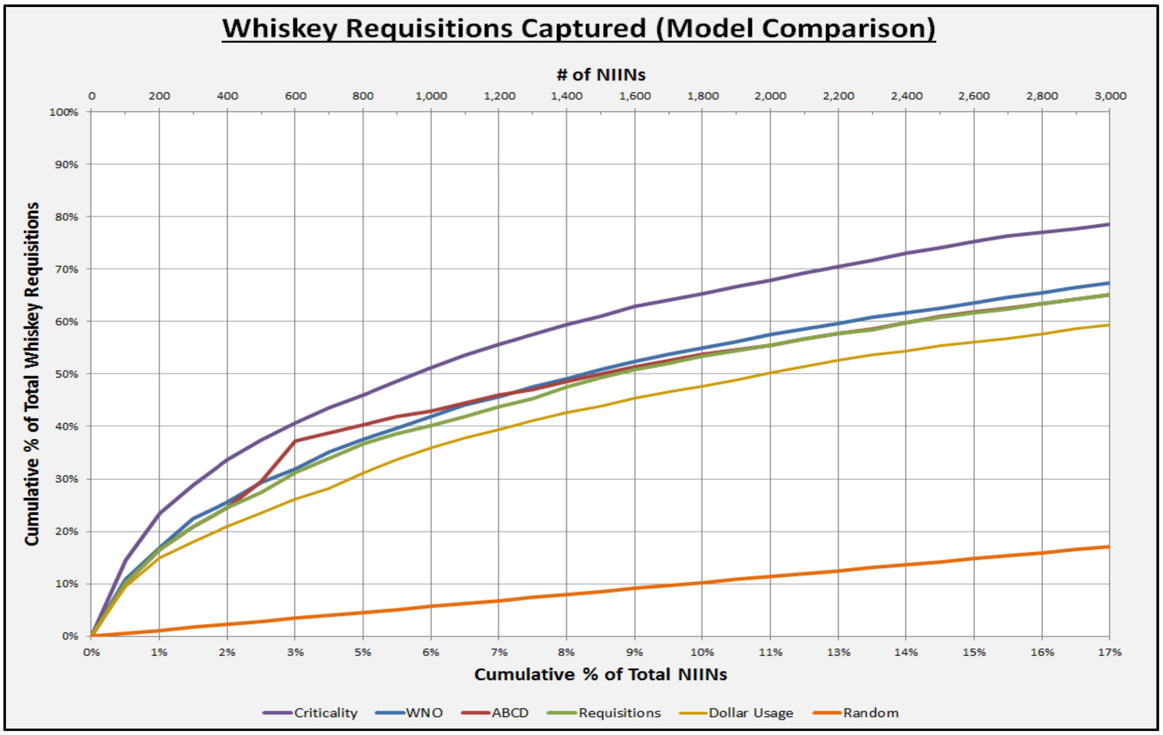

Figure 34. Comparison of cumulative % of total whiskey requisitions captured.

Four of the six models perform similarly in terms of requisitions captuerd. The Requisitions and ABCD model are requisitions-driven, so they each provide marginally better capture than the WNO and Criticality models. The significantly lower capture for the Dollar Usage model indicates that a large portion of fill rate would be lost with a Dollar Usage model implemenation. Figure 35 shows the requisitions captured model comparison results.

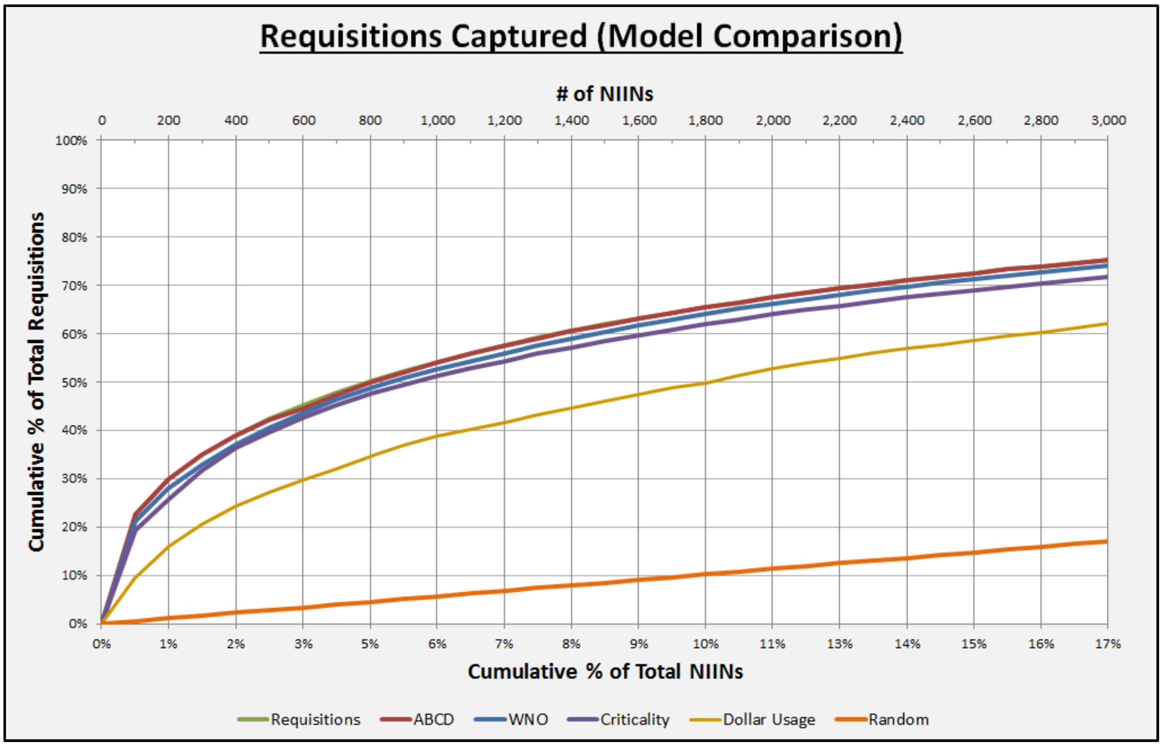

Figure 35. Comparison of cumulative % of total requisitions captured.

Requisition variance is a measure of requisition volume uncertainty. Requisition variance is somewhat correlated with requisition volume, so the relative order of model performance is somewhat close to that of the requisitions capture. Figure 36 shows the cumulative requisition variance capture for each model. Unlike the other models, the WNO model directly accounts for requisition variance. It proves to be the best model for requisition variance capture.

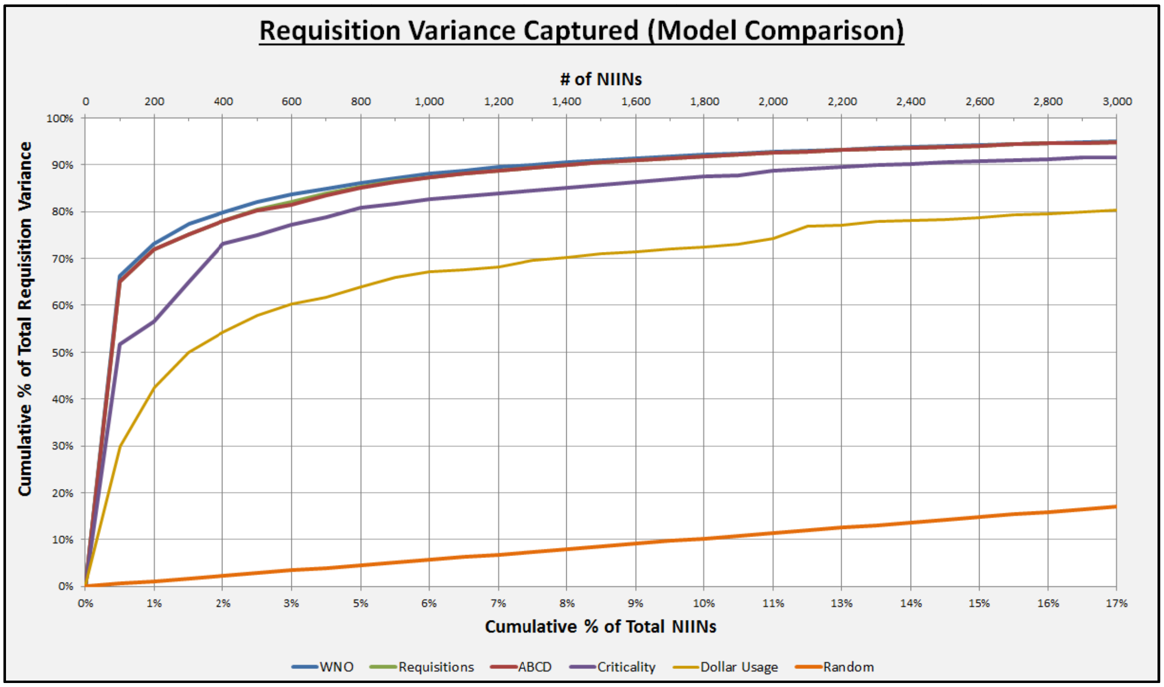

Figure 36. Comparison of cumulative % of total requisition variance captured.

Quantity demand is strongly correlated with requisition volume and dollar usage. Instead of treating two requisitions equally, it considers the volume of units demanded by all requisitions. The WNO model is the only one that considers both requisition volume and dollar usage, so it again proves to be the best performer. Figure 37 shows that the WNO model captures approximately 14% more quantity demand than the Requisitions and ABCD model at the 400-NIIN mark, which is very significant.

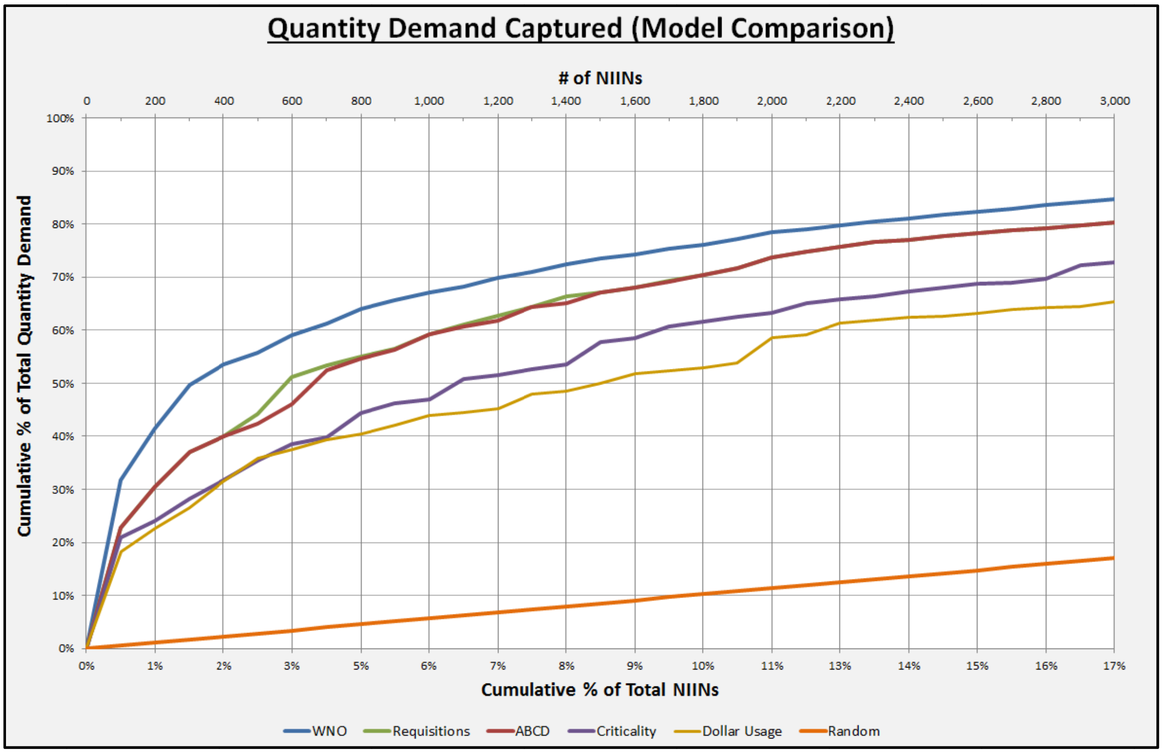

Figure 37. Comparison of cumulative % of total quantity demand captured.

PPV factors in more qualities than any other metric. Demand, multiple lead times, and repair pipeline loss rate all major factors. PPV also represents the most likely metric that WSS has the ability to improve. As shown in Figure 38, the WNO model again outperforms all other models. It captures approximately 20% more PPV than the Requisitions and ABCD models at the 300-NIIN mark. If considering the Requisitions and ABCD capture as a basis, WNO captures nearly 70% more PPV at that point.

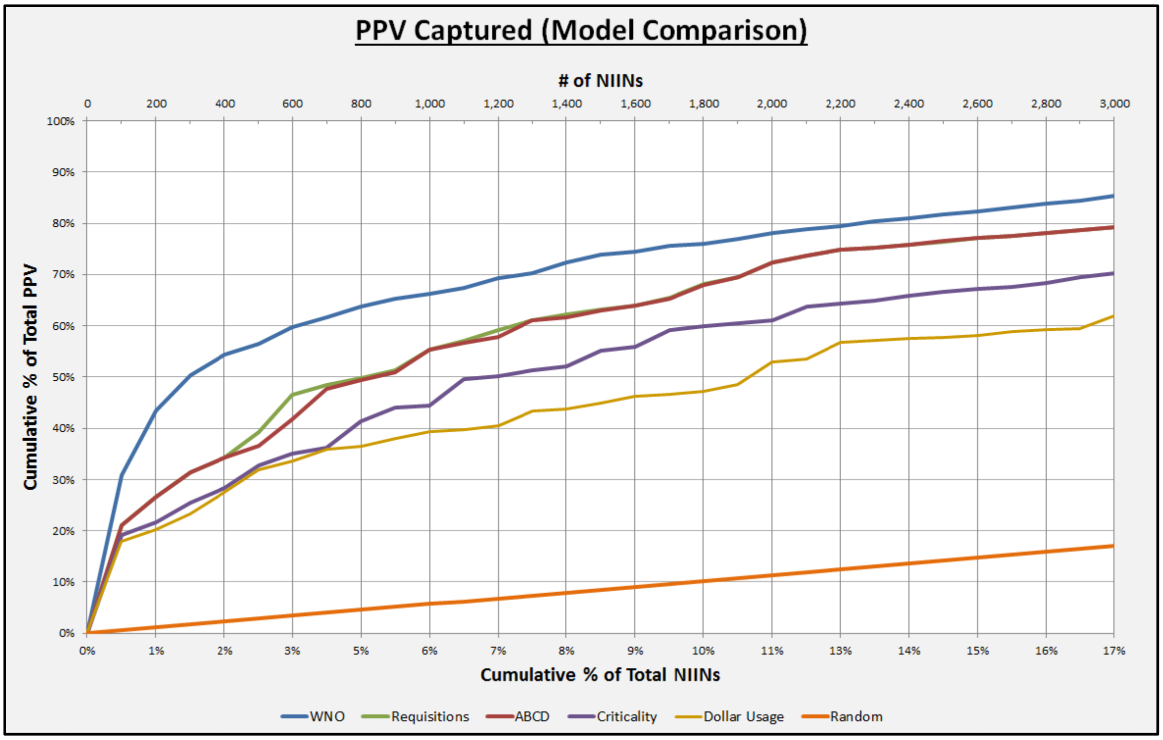

Figure 38. Comparison of cumulative % of total PPV captured.

As with the requisition variance metric, PPV variance measures the unpredictability in PPV. More so than with the other metrics, there is a very small portion of NIINs that account for the majority of the metric. As shown in Figure 39, just 200 NIINs account for more than 55% of PPV Variance in all models but Random. The WNO again significantly outperforms all other models. At the 300-NIIN mark, WNO captures approximately 90% of PPV Variance whereas the Dollar Usage, Requisitions, ABCD, and Criticality models each capture approximately 60%.

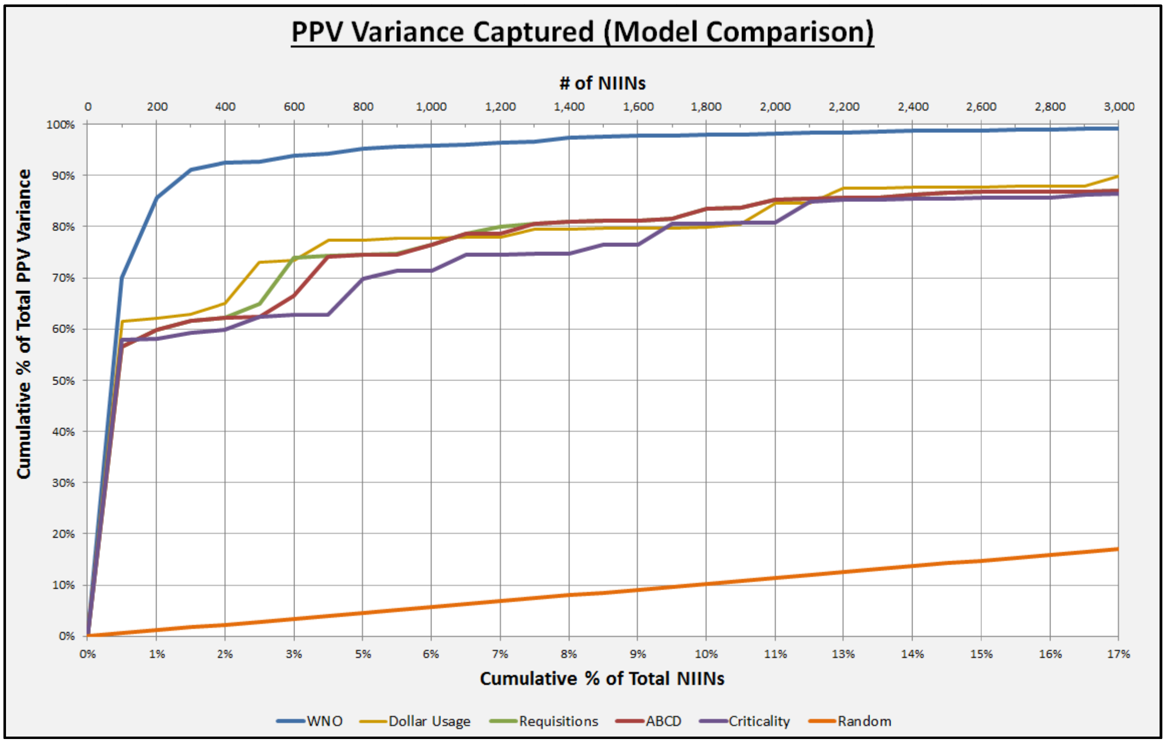

Figure 39. Comparison of cumulative % of total PPV variance captured.

Each model contains its own pros and cons based on the specific metrics being measures. The WNO model proves to perform consistently well compared to all other models. It also displayed some of the largest performance gaps over the other models, especially in the quantity demand, PPV, and PPV variance measures.

E. SENSITIVITY ANALYSIS

Time frames of 24 months for regular requisitions and 12 months for whiskey requisitions are used in this analysis due to numerous management reasons. Various time frames were also analyzed to understand how differences can affect model performance. Combinations of time frames ranging from 36 months to 6 months for each type of requisition were considered. The analysis shows that percentage of capture among each of the metrics did not change much. Though many combinations were analyzed, two specific examples are provided. Relative to the baseline of 24/12 (24-month requisitions and 12-month whiskey requisitions) shown in Figure 16, the metric capture increase and

decrease results for 36/24 and 18/6 time frames are shown in Tables 17 and 18. The small differences prove to be relatively insignificant.

Model Solution (24/12)							
	500	750	1000	1500	2000	2500	3000
Reqs	40.55%	47.40%	52.63%	60.30%	66.10%	70.56%	74.03%
ReqVar	81.99%	85.60%	88.08%	91.00%	92.74%	94.02%	94.95%
PPV	56.42%	63.38%	66.32%	73.80%	78.10%	81.71%	85.37%
PPV.Var	92.64%	94.71%	95.74%	97.57%	98.22%	98.75%	99.11%
W	29.28%	36.22%	41.90%	50.81%	57.50%	62.62%	67.42%
HP	36.56%	43.52%	48.62%	56.73%	62.76%	67.49%	71.30%
IMEC (4)	4.86%	7.04%	9.27%	13.67%	17.47%	20.99%	24.38%
DolUse	45.21%	51.56%	56.87%	65.04%	71.23%	75.44%	79.17%

Table 16. Results of WNO NIIN prioritization using 24/12 (24 months of requisitions and 12 months of whiskey requisitions).

WNO Timeframes: (36/24) vs. (24/12)							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	0.72%	0.74%	0.59%	0.57%	0.63%	0.75%	0.95%
Reqs Var	2.41%	1.77%	1.32%	0.93%	0.83%	0.73%	0.66%
PPV	1.28%	0.28%	1.47%	0.83%	1.25%	1.33%	0.37%
PPV Var	1.22%	0.84%	0.41%	0.36%	0.34%	0.25%	0.06%
W	-0.84%	-1.00%	-0.96%	-1.27%	-1.21%	-1.48%	-2.16%
HP	-0.71%	-1.03%	-1.10%	-1.31%	-1.31%	-1.61%	-1.44%
IMEC-4	-0.08%	0.04%	0.08%	-0.06%	0.04%	0.20%	0.26%
Dollar Usage	-0.26%	0.03%	-0.11%	-0.09%	-0.20%	0.03%	-0.04%

Table 17. Comparison results of WNO NIIN prioritization using 36/24 instead of 24/12.

WNO Timeframes: (18/6) vs. (24/12)							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	-0.05%	-0.08%	-0.04%	0.01%	0.01%	-0.05%	0.03%
Reqs Var	0.10%	-0.05%	-0.07%	-0.01%	0.01%	0.00%	-0.01%
PPV	-0.34%	-0.20%	-0.25%	-0.87%	-0.40%	-0.30%	-0.40%
PPV Var	-0.07%	0.40%	-0.04%	-0.12%	-0.05%	-0.04%	-0.03%
W	-0.29%	-0.43%	-0.15%	-0.19%	-0.22%	-0.35%	-0.82%
HP	-0.40%	-0.52%	-0.58%	-0.69%	-0.68%	-0.70%	-0.71%
IMEC-4	-0.04%	-0.16%	-0.24%	-0.31%	-0.28%	-0.26%	-0.31%
Dollar Usage	-0.09%	0.29%	0.22%	0.13%	0.04%	0.26%	0.10%

Table 18. Comparison results of WNO NIIN prioritization using 18/6 instead of 24/12.

F. ANALYSIS OF WNO VERSUS ABCD ON FUTURE REQUISITIONS

Two types of analysis are conducted to gauge the predictive abilities of each model. The first analysis considers a scenario where the WNO and ABCD models are employed to rank NIINs using data from an 18-month time frame. Those rankings are then used to determine each model's metrics capture of an ensuing 18-month time frame. The second analysis explores how the model rankings perform when measuring data not included in the original analysis and model build.

For the first analysis, data from the 18-month time frame of April 2011 through September 2012 is used to rank NIINs. Specifically, sales document data for that time frame and wholesale file NIIN data from September 2012 are used. For the WNO model, NIINs are ranked based on the newly generated scores. The metrics capture results for the WNO model over the initial 18-month timeframe are shown below in Table 19. For comparison purposes, the metrics capture results for NIINs ranked by requisition and whiskey volume are also generated. The exact ABCD model parameters are not used because they are built for a 24-month requisitions volume time frame rather than the 18-month time frame used in this analysis. The NIIN rankings for both models are then applied to sales document data for the ensuing 18-month time frame of October 2012 through March 2014 and the wholesale file NIIN data from March 2014. Table 20 shows how much of each metric was captured during the new time frame for the WNO rankings.

The tables show that the metrics capture does decrease slightly. The metric capture differences between the WNO model and the requisition and whiskey volume model shown in Table 21 are consistent with the results from previously analyzed timeframes. Small improvements over the WNO model in a couple of metrics are countered by significant losses in other metrics.

WNO (Apr11 - Sep12)							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	41.91%	48.63%	53.78%	61.43%	67.39%	71.82%	75.43%
Reqs Var	86.30%	88.79%	90.42%	92.74%	94.20%	95.19%	95.95%
PPV	59.34%	66.99%	71.95%	79.80%	84.21%	86.79%	89.05%
PPV Var	94.12%	96.44%	97.30%	98.42%	98.88%	99.25%	99.51%
W	32.08%	39.36%	44.70%	53.37%	60.21%	65.88%	70.61%
HP	37.96%	44.42%	49.50%	57.32%	63.56%	68.67%	72.70%
IMEC-4	5.80%	8.03%	10.31%	14.85%	19.36%	23.25%	26.52%
Dollar Usage	44.38%	50.78%	56.22%	64.43%	70.38%	75.60%	79.48%

Table 19. Results of WNO NIIN prioritization using data from April 2011—September 2012.

WNO (Oct12 - Mar14)							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	36.72%	43.13%	47.98%	55.11%	60.47%	64.33%	67.60%
Reqs Var	74.94%	78.23%	80.68%	83.91%	85.87%	87.15%	88.29%
PPV	53.96%	59.80%	63.13%	72.24%	76.37%	78.33%	80.32%
PPV Var	81.95%	83.02%	83.51%	86.67%	87.15%	87.31%	87.46%
W	26.94%	32.57%	37.58%	45.15%	50.72%	55.85%	59.35%
HP	33.78%	39.13%	43.80%	50.95%	56.41%	60.52%	63.76%
IMEC-4	4.94%	7.34%	9.62%	13.69%	17.94%	21.52%	24.73%
Dollar Usage	36.55%	42.32%	47.53%	54.67%	59.88%	64.04%	67.41%

Table 20. Results of WNO NIIN prioritization using data from October 2012—March 2014.

WNO vs Req/W Volume (Oct12 - Mar14)							
	# of NIINs (Highest Ranked)						
	500	750	1000	1500	2000	2500	3000
Reqs	1.77%	1.84%	1.59%	1.42%	1.28%	1.31%	1.20%
Reqs Var	-1.23%	0.77%	0.53%	0.24%	0.32%	0.27%	0.47%
PPV	-14.55%	-16.44%	-12.18%	-6.17%	-3.34%	-3.16%	-3.34%
PPV Var	-16.73%	-16.82%	-13.38%	-4.99%	-1.77%	-1.78%	-1.76%
W	-1.20%	-0.86%	-0.85%	-1.30%	-0.68%	-0.71%	-0.36%
HP	-0.24%	0.30%	0.25%	0.23%	0.00%	0.26%	0.36%
IMEC-4	0.24%	0.41%	0.35%	0.22%	0.31%	0.47%	0.43%
Dollar Usage	-6.53%	-6.41%	-6.09%	-7.21%	-7.27%	-6.53%	-6.02%

Table 21. Comparative results of using a requisition and whiskey volume prioritization model instead of the WNO model for two sequential 18-month timeframes.

The second analysis explores how the models perform when applied to data not included in the original WNO model build. The data used to build the WNO model includes sales document data from April 2011 through March 2014. More recent sales document data from the period of April through June of 2014 is now used for predictive analysis of how the models might perform in the future. With such a short time frame and small sample size, the scope is extremely limited. In theory, a model would have prioritized NIINs for resource allocation back in April of 2014, and then WSS planners and contracting specialists would have focused on placing optimal controls on the high-priority NIINs. Because that has not happened in the span of this study, using a recent 90 days of sales data to compare models might provide a bit of insight of future model performance.

Sales document data for three months from April through June of 2014 is gathered and analyzed. The analysis focuses on comparing the two most likely models to be implemented by WSS, that is: WNO and ABCD. The analysis hones in on the sales data of NIINs that were classified differently between the two models. Based on ABCD criteria and the 24-month requisition time frame, 570 NIINs would be classified as "A," 636 as "B," 1319 as "C," and the remainder as "D." The same numbers of NIINs were assigned to each category based on WNO model prioritization. As with the prior analysis, family member NIIN data are rolled up into and represented by the family head

NIIN. Also, because the ERP wholesale file has not updated since the prior analysis, IMEC, prices, PPV, and PPV variance have not changed. Lastly, as with the original analysis, only the requisitions for NIINs that compete for WSS resources are analyzed.

Over the three-month period, there were 19,078 requisitions for the 5,245 NIINs that compete for WSS resources. Of those requisitions, only 5.6% (1,075) of them were for NIINs that were classified differently by the WNO and ABCD models. Those 1,075 requisitions were spread out among 413 different NIINs. Figure 40 shows the classification differences between the two models. 19 of the requisitions were classified as "A" by WNO versus "D" by ABCD, 227 were classified as "B" by WNO versus "C" by ABCD, 24 were classified as "B" by WNO versus "D" by ABCD, 254 were classified as "C" by WNO versus "D" by ABCD, and 551 were classified as "D" by WNO versus "C" by ABCD.

Requisitions Misclassification (WNO vs ABCD)					
		ABCD Class			
WNO Class		A	B	C	D
	A		0	0	19
	B	0		227	24
	C	0	0		254
	D	0	0	551	

Figure 40. NIIN classification differences between WNO and ABCD models for requisitions from April through June of 2014.

Figure 41 displays the fill rates for each group of the misclassified requisitions. Though each of the categories achieved low fill rates, the WNO model's "A" and "B" categories were much lower than the others. These NIINs were prioritized high in the WNO model not because of requisition volume, but because of other variables, namely dollar usage, variance, and PPV measures. The model identified that the unpredictability, quantity, price, and lead times associated with these NIINs should prioritize them over the stability of higher requisition NIINs. An example of a NIIN classified as "A" by WNO and "D" by ABCD is one that had only 11 requisitions and 0 whiskey requisitions over the 24-month timeframe. While ABCD classified it as a "D" because of its low

requisition volume, WNO classified it as an “A” due to its extremely high dollar usage. Considering its demand of 11, pipeline loss rate of .99, and replacement price of $106,000, the item’s dollar usage was $1.15 million. The item had a demand of 3 over the recent 3-month time frame. Though the abnormally high demand for the short time period may have been difficult to forecast, the high WNO classification would have at least identified the item as one for its planner to closely monitor and optimally manage due to the strong budget impact potential.

Avg Fill Rate by Category				
	WNO		ABCD	
	Reqs	Fill Rate	Reqs	Fill Rate
A	19	0.500	0	0.000
B	251	0.465	0	0.000
C	254	0.530	778	0.649
D	551	0.680	297	0.524

Figure 41. Fill rate measures for each category of the different classifications.

The cumulative metric capture of the WNO and ABCD models for the time frame of April 2014 through June 2014 are shown in Tables 22 and 23. Again, the PPV, PPV variance, and prices are the same as in the previous analysis. As can be expected considering such a short time frame, the percentages are very similar. The majority of measures for each model are within 2% of each other. Besides the unaltered PPV and PPV variance metrics, the major difference is dollar usage. An approximate dollar usage advantage of 36% over the ABCD model (using the ABCD result as a basis) for the top 500 NIINs is a significant difference and one that could have fostered more efficiency in WSS budget allocation.

WNO Solution							
	500	750	1000	1500	2000	2500	3000
Reqs	41.15%	48.46%	54.18%	63.40%	70.39%	76.41%	81.75%
ReqVar	74.65%	78.79%	81.26%	86.76%	89.13%	91.23%	94.54%
PPV	70.20%	76.88%	80.57%	87.21%	92.77%	95.60%	97.70%
PPV.Var	96.25%	97.64%	98.10%	98.72%	99.60%	99.82%	99.95%
W	28.15%	36.21%	41.97%	54.11%	63.33%	70.85%	76.61%
HP	37.50%	44.45%	49.62%	59.30%	66.58%	73.00%	78.29%
IMEC (4)	12.76%	18.77%	25.42%	36.14%	46.33%	55.50%	65.09%
DolUse	45.66%	52.46%	58.99%	67.83%	74.97%	80.51%	85.32%

Table 22. WNO model results, based on requisitions from April through June of 2014.

ABCD Solution							
	500	750	1000	1500	2000	2500	3000
Reqs	41.97%	48.95%	54.59%	64.12%	70.87%	76.83%	81.62%
ReqVar	73.76%	77.46%	79.11%	86.83%	89.28%	91.46%	92.97%
PPV	44.14%	59.93%	67.69%	80.08%	87.08%	91.59%	95.33%
PPV.Var	65.79%	78.42%	80.59%	85.60%	87.66%	91.87%	99.37%
W	29.42%	36.10%	40.90%	53.19%	61.64%	69.24%	75.19%
HP	38.28%	44.22%	48.82%	58.75%	66.01%	72.60%	77.56%
IMEC (4)	13.51%	20.00%	25.74%	36.57%	47.08%	56.62%	66.06%
DolUse	33.65%	41.30%	46.15%	55.75%	62.24%	69.91%	77.23%

Table 23. ABCD model results, based on requisitions from April through June of 2014.

The limited scope of this analysis significantly limits the weight it should be given. It does show, however, that minor deterioration in the capture of a couple of metrics lead to significant improvements in the capture of other metrics. These results are consistent with the larger scale analysis used to build the models. Additionally, the budgeting efficiency tied to tightening controls on high PPV and dollar usage items should lead to higher requisition capture over time. A better idea of the effects of those tighter controls can be explored through advanced simulation models and further analysis.

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V. CONCLUSION AND RECOMMENDATIONS

A. CONCLUSIONS

Decades of research and analysis has shown that ABC analysis is a viable concept that should be employed in nearly any inventory management system. The criteria used to prioritize inventory should be representative of business goals. For WSS, these goals include fill rate and operational readiness. Fill rate is a direct function of demand and inventory on hand, while operational readiness is based on both demand and the criticality measures of that demand. While WSS cannot change business rules or prioritize NIINs in an effort to directly impact demand, it can impact the amount and stability of inventory on hand. Regression analysis, in the form of random forests, identified variables associated with demand, lead time, and price as the inventory qualities strongly affecting fill rate. Subject matter expertise was used to identify variables representing criticality measures and to create criticality factors for ABC analysis.

Of all explored ABC analysis methods, the multi-criteria weighted non-linear optimization technique proved to be the best option for WSS's NIIN prioritization goals. It optimally assigns weights to priority-ranked NIIN factors so as to maximize the summation of factor-based scores across all NIINs being ranked. This technique identifies the order in which NIINs should be optimally managed based on the priorities specified. The model maximizes the cumulative capture of each factor as NIINs are added to the list in prioritized order.

A model based on WNO was built in Microsoft Excel and used to prioritize the NIINs competing for WSS resources. Requisition volume, requisition variance, criticality, dollar usage, PPV, and PPV variance were the metrics considered in the model for prioritization. Cumulative metric capture was used to compare the WNO model results with alternative prioritization schemes such as ranking via ABCD, requisitions volume, criticality, dollar usage, and randomness. Though four of these models slightly outperformed WNO in one or two measurements, WNO was by far the best modeling

method from a holistic approach. Relative to each of the other models, slight losses in WNO capture of a few metrics was countered with significant gains in other metrics.

Sensitivity analysis was also conducted on the WNO modeling approach. Different time frames were considered in addition to the baseline 24-month requisition and 12-month requisition data. The sensitivity analysis ranged from 36 months of data down through 6 months of data. The analysis showed only slight changes in terms of metric capture.

Analysis was also conducted on the predictive abilities of the WNO and ABCD models. Sales document data was collected for the three-month time frame following the time frame used for the original NIIN category assignments. 270 requisitions were received for NIINs categorized as "A" or "B" by WNO, but "C" or "D" by ABCD. WSS achieved a fill rate far below its average on those requisitions. None of the requisitions received were categorized as "A" or "B" by ABCD but "C" or "D" by WNO. Though the analysis is limited in scope, it provides a sample of the value added by prioritization based on more than just requisition volume.

B. RECOMMENDATIONS

As opposed to WSS's historical FIFO process, any NIIN prioritization scheme that considers at least requisition volume should provide increases in fill rate and operational readiness. The most immediate increases in fill rate would result from the models that are squarely focused on requisition volume, such as the ABCD and Requisitions models. Though these models will meet short-term objectives, their utilization is not the best long-term approach for WSS. Unlike other options, WNO attacks the underlying drivers of fill rate while maintaining focus on operational readiness.

The consideration of requisition variance, lead times, and dollar usage fosters inventory stability and the efficient use of a constrained inventory budget. Inventory level stability is aided by predictable and stable lead times, which can be improved through item manager and contracting specialist attention. Inventory budget efficiency is aided by limiting the dollar value of on-hand inventory, which can be improved through

tighter controls and strict oversight from item managers and contracting specialists. As efficiencies improve in budget allocation, additional budget is available for allocation towards the lower demand items for which planning is so difficult.

The flexibility to drive the WNO model using any number of factors is yet another feature superior to the other models. WSS managers are able to choose other measures and the priorities of those measures to use in the model. Though solely ranking NIINs based on requisition volume is discouraged, the WNO model can be easily tailored to prioritize based on just that criterion.

There is no downside to implementing the WNO modeling approach into WSS NIIN prioritization. Its flexibility, compatibility, and ability to optimize based on multiple criteria render it the superior model. WSS would be best served, from a long-term and holistic approach, by using the six criteria suggested for the proposed WNO model. Though only time will tell how much the fill rate and operational readiness will improve with its implementation, theory and analysis suggests the improvements could be significant.

C. FUTURE RESEARCH

Numerous avenues are available for future research and/or application of the WNO modeling approach as it pertains to the WSS business. The scope of this study consists only of maritime NIINs and wholesale maritime demand of those NIINs. Other areas to consider are aviation NIINs, aviation wholesale demand, and both aviation and maritime retail demand. Aviation NIINs require a large portion of WSS resources and can have significantly different attributes than maritime NIINs. The application of the WNO model to aviation NIIN prioritization, albeit with different model factors, could provide comparable value seen by its application to maritime demand.

WSS is responsible for all parts support of naval forces, regardless of the level at which that support is required. For each naval command, parts are stored, requisitioned, and issued at both the retail and wholesale levels. The majority of inventory parts issued to fill requisitions at the retail level are replenished through requisitions on the wholesale level. While criticality measures are easy to obtain on the wholesale level (via whiskey

requisitions and priority levels), they are difficult to obtain on the retail level. Additionally, the accuracy of the criticality measures that are obtainable from retail requisitions is very questionable. Much value could come from analyzing ways to incorporate and combine retail demand and criticality measures into the wholesale WNO model. This analysis would be applicable to the realms of both maritime and aviation parts support.

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